Estimation of Built Up Areas from High Resolution Remote Sensing Images

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Abstract— **In this work an unsupervised approach is used which detect the build up area from a single image . The motivation behind is that the frequently recurring appearance patterns or repeated textures corresponding to common objects of interest in the input image data set can help discriminate built up areas from others. Major approaches for built up area detection are based on texture analysis. The earlier existing methods have their own pros and cons, their main limitation is that they are supervised and need training sample images to detect built up areas. The implemented method divided into two steps. First extract a large set of corners from each input image by an improved Harris corner detector. Afterward, incorporate the extracted corners into a likelihood function to locate candidate regions in each input image. Given a set of candidate built-up regions, in the second stage, formulate the problem of discovering the frequently recurring texture patterns corresponding to built up areas as an unsupervised grouping problem. To do this model the candidate regions with corresponding histogram representation of texture feature , and grouping problem can be solved by using spectral clustering and graph cuts. To measure the performance of this system it is tested over for 30 different satellite images of 1 meter resolution. The detected built up areas are compared with ground truth(marked manually). by using True Positive Rates, False Positive Rates**

Index Terms—**Built-up area detection, corner detector, unsupervised approach, spectrum clustering.**

I.INTRODUCTION

With the development of remote sensing technologies, high resolution sensing images have become critical sources of information in diverse fields such as geography, cartography, surveillance, city planning, and so on. Among them, monitoring the distribution, growth, and characteristics of built-up area receives a growing number of attentions for it can greatly help local agency to update land maps and draw city plans. In such applications, the basic but important step is to extract built-up regions from the high-resolution remote sensing images.

Generally, a built-up area represents a vital and highly dynamic environment which is mostly composed of both man- made and natural objects. Because the texture of the scene is distinct from that of the natural scene, major approaches for built-up area detection are based on texture analysis. Ünsalan and Boyer [1] combine line-support regions with spectral fea- tures to measure built-up areas. Pesaresi and Benediktsson [2] introduce a novel mathematical morphological transformation, called differential morphological profile, to extract texture in- formation from the image. Its application for built-up region detection can be found in [3]. In their later work [4], a build- up area presence index is proposed for built-up area extraction in panchromatic satellite image, which is based on fuzzy- rule-based composition of anisotropic texture co-occurrence measures. In recent years, built-up area detection based on local invariant features has revealed promising results. In [5], 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 complex- ity and memory requirement. In their later work [6], a more direct method is used. However, since it solely depends 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.

When given a lot of remote sensing images for urban information analysis, we can observe that there are many frequently recurring appearance patterns or repeated textures corresponding to common objects of interest (e.g., built-up area), which is a significant discrimination property to help us discern built- up area from others. Inspired by this idea, we present an un- supervised approach to simultaneously detect built-up regions from multiple high-resolution remote sensing images—to our knowledge, the first approach proposed for this problem using such an idea. In our method, we take a built-up region as a common object that appears frequently in the input image data set and use the cues extracted and integrated from multiple images to infer the location of built-up regions. To this end, the proposed approach is divided into two steps. First, we extract a large set of corners from each input image by an improved Harris corner detector. Afterward, we incorporate the extracted corners into a likelihood function to locate candidate regions in each input image. Given a set of candidate built-up regions, in the second stage, we formulate the problem of discovering the frequently recurring texture patterns corresponding to built-up areas as an unsupervised grouping problem. To do this, we model the candidate regions with histogram representation of texture feature and then solve the grouping problem by spectrum clustering and graph cuts.

II. CORNER DETECTOR

Many different interest point detectors have been implemented with a wide range of definitions for what points in an image are interesting. Some detectors find points of high local symmetry; others find areas of highly varying texture, while others locate corner points.Corrner points are interesting as they are formed from two or more edges and edges usually define the boundary between two different objects or parts of the same object.

If we could detect all such corner points from images, the built-up regions would be naturally implied from the density of corners. Thus, in this section, we use the corner feature to infer the locations of potential built-up regions in the given images. Corner detection has been a long- standing problem in computer vision. In the literature, a large number of methods have been proposed, and the most famous one should be Harris corner detector [7]. However, previous study [8] shows that Harris detector is not well suited for the application of built-up area detection, since it is sensitive to the texture areas and easily mistakes edgelike points as true corner points. In order to achieve a reliable extraction of corners from built-up areas, we proposed two criterions, which take both local and global constraints into consideration, to validate and filter a large set of initial extracted Harris corners.

III.THE MULTI-SCALE HARRIS OPERATOR

The computation of the second moment matrix (sometimes also referred to as the structure tensor) A in the Harris operator, requires the computation of image derivatives I_x, I_y in the image domain as well as the summation of non-linear combinations of these derivatives over local neighborhoods. Since the computation of derivatives usually involves a stage of scale-space smoothing, an operational definition of the Harris operator requires two scale parameters:

(i). a local scale for smoothing prior to the computation of image derivatives, and

(ii). an integration scale for accumulating the non-linear operations on derivative operators into an integrated image descriptor.

Then, we can compute eigen values of μ in a similar way as the eigen values of A and define the multi-scale Harris corner operator or detector measure as

$$M_c(x,y;t,s) = \det(\mu(x,y;t,s)) - \kappa\ \mathrm{trace}^2(\mu(x,y;t,s))$$

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to analyze multi-scale HARRIS operator the Estimation of Built Up Areas from multiple high-Resolution Remote Sensing Images. Generally, a built-up area represents a vital and highly dynamic environment which is mostly composed of both man- made and natural objects. Because the texture of the scene is distinct from that of the natural scene, major approaches for built-up area detection are based on texture analysis.

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A. Local Constraint

Let $D = \{p_i | 1 \le i \le N_1\}$ be a set of N_1 initial corners produced by the Harris detector. The local constraint is based on the observation that, if p_i is a corner point from a man-made object, it should be the intersection of two nearly orthogonal contours. With this inspiration, we first use Canny edge detector to extract contour fragments in the given image and then approximate each contour c_i as one or several line segments through the Douglas-Peucker algorithm [9]. For each corner point $p_i \in D$, let l_1 and l_2 be the two nearest line segments from it and θ_i be the angle between the line segments l_1 and l_2. As mentioned previously, if p_i is a corner point from a man-made object, it should be the intersection of two nearly orthogonal contours. Thus, we propose the first criterion of refinement:

$$|\theta_i - 90^\circ| < \sigma_1$$

where σ_1 is a control threshold. θ_i is the angle between the line segments l_1 and l_2 associated with p_i. A corner will be pruned if it does not satisfy the first criterion.

B. Global Constraints

Moreover, considering the densely distributed characteristic of corners in the built-up region, we should take density of corners into consideration. Obviously, it is easy to measure by counting the number of corners in a corner's neighborhood. Therefore, except evaluating individual p_i, we also evaluate its neighborhood N_{p_i}, which is a circle with radius r around p_i. For each p_i, we define its neighborhood corner set as

$$M_{p_i} = \{p_j | \mathrm{dist}(p_j - p_i) < r,\ p_j \in D\}$$

IV IMPLEMENTED METHOD

Fig.1 input high resolution remote sensing image

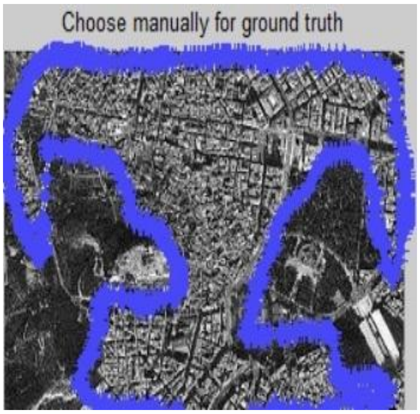

Fig.2 manually labeled Ground truth of input image.

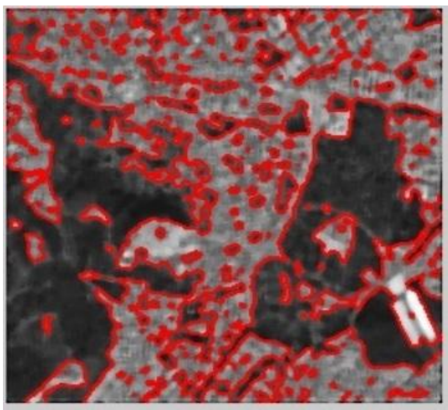

Fig. 3 output image of implemented method.

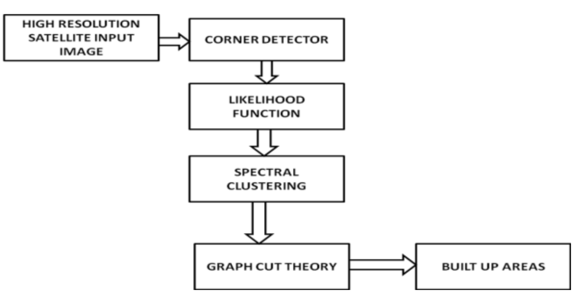

Fig.4. The block diagram of implemented method for estimation of built up areas

A.LIKELIHOOD FUNCTION

Generally, corners in the built-up area tend to closely locate in the neighboring spatial domain with high density. For a non-built-up area, these corners are more likely to be sparsely distributed. This means that, if an image pixel (xi, yi) belongs to a built-up area, expect that there are more corner points in its neighborhood. With this observation, define the following likelihood function to measure the possibility that a pixel (xi, yi) belongs to a built-up area:

$$LS(x_i, y_i) = \sum_{k=1}^{N_2} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\sqrt{(x_i - x_k)^2 + (y_i - y_k)^2}}{2}\right)$$

where (xk, yk) represents the spatial coordinate of the extracted N2 corner points, for k = 1 ,..., N2.

The likelihood function highlights the built-up region in the pixel neighborhood. If it is a good candidate for the built-up region, a high value LS(xi, yi) is expected.

B.FEATURE EXTRACTION OF CANDIDATE BUILT-UP REGIONS

The built-up region has unique texture in comparison with a natural area, here, use the texture feature to describe the built-up region. In this work, the texture feature is obtained by the following three steps:

i. Gabor filter with adaptively chosen size, orientation, frequency and phase for each pixel. Characteristic features related to the change in brightness, color, texture and position are extracted for each pixel at the selected size of the filter. In order to cluster the pixels into different regions

The Gabor filter bank is as follows

$$\psi(x, y) = \frac{f^2}{\pi\gamma\eta} e^{-\left(\frac{f^2}{\gamma^2}x'^2 + \frac{f^2}{\eta^2}y'^2\right)} e^{j2\pi f x'}$$
$$x' = x\cos\theta + y\sin\theta$$
$$y' = -x\sin\theta + y\cos\theta \quad .$$

Where,

θ - orientation , f – frequency , γ : aspect ratio

The above equation is centered to the origin and filter response of Gabor filter can be expressed by using the following equation.

$$G_{x,y} = \exp\left(-\frac{(x\cos\theta + y\sin\theta)^2 + \gamma^2(-x\sin\theta + y\cos\theta)^2}{2\sigma^2}\right) \times \cos\left(2\pi\frac{1}{\lambda}(x\cos\theta + y\sin\theta) + \phi\right).$$

The biggest problem of clustering is that it suffers from determining the number of clusters in an unsupervised clustering scheme which is known as cluster validity. The implemented scheme is an unsupervised image segmentation technique where the number of clusters is determined automatically based on the problem at hand.

(ii). The resultant filter responses are aggregated and clustered into textons by using k-means algorithm.

k-means algorithm used for clustering textons into clusters on the basis Euclidean distance. The textons grouped into several clusters on the basis their Euclidean distance by using the k-means algorithm.

(iii). A *k*-dimensional histogram descriptor h_i is constructed for each candidate region R_i by labeling each filter response with the texton which lies closest to its texton dictionary.

C.SPECTRAL CLUSTERING

The clustering problem can be solved by using spectral clustering. Spectral clustering method to solve the grouping problem. In recent years, spectral clustering has become one of the most popular modern clustering algorithms. It is simple to implement and outperforms traditional clustering algorithms such as the *k*-means algorithm. Generally, it consists of the following four steps.Suppose that there are *M* built-up samples extracted from the input image collection in the first stage, and

$\mathbf{H} = \{\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_M\}$ denotes their corresponding texture histogram. The first step is to calculate an $M * M$ affinity matrix $\mathbf{A} = \{A_{ij}\}$

where the entries A_{ij} measure the affinity between the ith and jth feature vectors.
Here, A_{ij} is defined as follows:

$$S(r_i, r_j) = K_{\chi^2}(\mathbf{h_i}, \mathbf{h_j})$$

Where $\mathbf{h_i}$ and $\mathbf{h_j}$ denote the texture feature histograms extracted from the candidate regions R_i

D.GRAPH THEORY

After grouping the candidate regions into several clusters, the final step is to identify which clusters are corresponding to the built-up region. Ideally, expect that all the built-up regions would be grouped into one cluster since they belong to the same category. In practice, due to the intra class variations, they may be grouped into one or several clusters. To handle this, first formulate the classification problem as a labeling problem, i.e., assigning each cluster C_i with a label $L(C_i)$ as follows

$$L(C_i) = \begin{cases} 1, & \text{if } C_i \in \text{built-up region} \\ 0, & \text{if } C_i \in \text{non-built-up region.} \end{cases}$$

Define the cost function for labeling Built up areas

$$E(L) = \sum_i V_d(C_i, L(C_i)) + \sum_{i \neq i} V_s(C_i, C_j, L(C_i), L(C_j))$$

The possibility of each cluster belonging to built up areas can be measured by

$$V_d(C_i, L(C_i)) = \begin{cases} 1 - N_{C_i}/M, & \text{if } L(C_i) = 1 \\ N_{C_i}/M, & \text{if } L(C_i) = 0 \end{cases}$$

Where M is the total number of the candidate built-up regions and N_{C_i} denotes the region number in cluster C_i.

V.RESULT ANALYSIS:

Experimental results show that the implemented approach outperforms the existing algorithms in terms of detection accuracy the existed methods need some building samples to performs the detection of built up areas. But in this implemented method no need to give any input samples to detect built up areas from given input image. The implemented method is applicable for high resolution remote sensing images. The high resolution remote sensing images give more information to detect built up areas. These high resolution remote sensing images has more details by showing buildings corners, roads, gardens etc which are more useful to detect build up areas. The results of this implemented method explained in

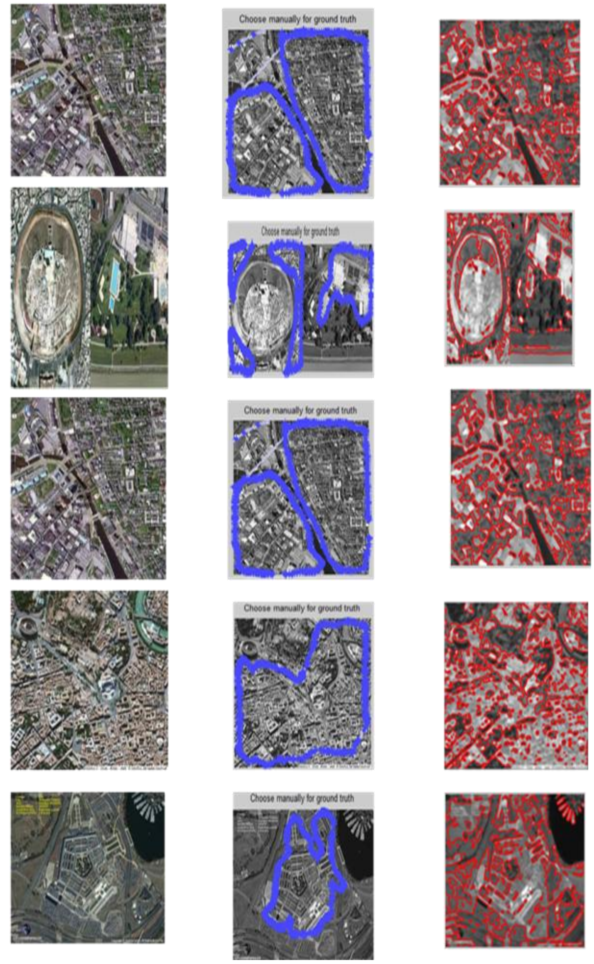

Fig.5. consists of five images with input image, ground truth, output image respectively.

S.NO	BUILT UP PIXELS	HARRIS CORNER		FEATURE EXTRACTION	
		TPR	FPR	TPR	FPR
1	300	83.89%	6.12%	96.97%	2.26%
2	260	83.56%	6.86%	96.67%	2.07%
3	272	83.16%	6.58%	96.72%	2.13%
4	278	83.17%	6.26%	96.73%	2.37%
5	245	83.47%	6.16%	96.38%	2.17%
6	225	83.37%	6.85%	96.19%	2.32%
7	260	83.89%	6.12%	96.97%	2.26%
8	560	83.56%	6.86%	96.39%	2.07%
9	255	83.56%	6.38%	96.15%	2.11%
10	229	83.46%	6.26%	96.73%	2.37%

TABLE: I TPR & FPR of 1m spatial resolution images

In the above shows that the TPR of corner based detection can be shows good performance but FPR is little bit high that is the main limitation of corner based detection. The TPR of feature based extraction has good results comparing with corner based detection.

The above tables shows the results of high resolution remote sensing images with 1m spatial resolution with their corresponding TPR, FPR.

VI.CONCLUSION:

In this work presented an unsupervised framework for discovering built-up regions from multiple high-resolution satellite images. The implemented method includes two major components:

1) A likelihood function- based approach to extract candidate built-up regions, in which an improved Harris operation is implemented the corner points.

2) spectrum-clustering and graph cut based unsupervised clustering algorithm for the final built-up area detection. Based on the extensive tests, the implemented method approach demonstrates advantages over the previous works. First, it can detect built-up regions from high resolution images without need of any input templates, and experiment results show that the performance of built-up area detection is improved. Second, the time consumption for detection of built up areas from high resolution input images is also low as compared with existing methods.

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