

A new approach for Classifying land development in High-Resolution Remote Sensing Images

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ABSTRACT : In this paper present an unsupervised method for discovering compound image structures that are comprised of simpler primitive objects. An initial segmentation step produces image regions with homogeneous spectral content. Then, the segmentation is translated into a relational graph structure whose nodes correspond to the regions and the edges represent the relationships between these regions. Therefore, we employ two different procedures to discover the sub graphs in the constructed graph. During the first procedure the graph is discredited and a graph-based knowledge discovery algorithm is applied to find the repeating sub graphs. Even though a single sub graph does not exclusively correspond to a particular compound structure, different sub graphs constitute parts of different compound structures. 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. The second procedure involves graph segmentation by using normalized cuts. Since the distribution of significant relations within resulting sub graphs gives an idea about the nature of corresponding compound structure, the sub graphs are further grouped by clustering the histograms of the most significant relations.

Keywords- Built-up area detection, corner detector, graph cut, high-resolution remote sensing image, spectrum clustering.

I. INTRODUCTION

In This paper, a new segmentation method is proposed. The proposed method uses the residuals of morphological opening and closing transforms based on a geodesic metric. The proposed approach may be considered analogous to region growing techniques. However, in contrast to the use of statistical local properties as in region growing approaches, the proposed method uses a pixel similarity rule based on the morphological characteristic of connected components in images. In the proposed approach the morphological residuals between the original grey-level function and the composition of a granulometry and an anti-granulometry by reconstruction are used to build a morphological profile function. Recent theoretical advances in mathematical morphology, such as the definitions of leveling and the morphological spectrum, form a theoretical framework for the formal definition of the morphological profile function. This function is interpreted as a fuzzy membership function related to a set of morphological characteristics of the connected components in the image. A labeling phase is then formalized using a decision rule based on the greatest value of the derivative of the morphological profile function. As can be seen earlier, although existing methods have their own pros and cons, their main limitation is that they all focus on detecting build-up regions from a single image and thus have to label a large volume of training samples to provide sufficient prior information for high detection rate.

Generally, a built-up area represents a vital and highly dynamic environment which is mostly composed of both manmade 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

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regions with spectral features to measure built-up areas. Pesaresi and Benediktsson.[2] Introduce a novel mathematical morphological transformation, called different morphological profile, to extract texture information from the image. Its application for built-up region detection can be found in [3] their later work, [4] a built-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 complexity 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.

II. EXTRACTION OF CANDIDATE BUILT-UP REGIONS

Given a set of high-resolution remote sensing images covering different scenes, our objective is to simultaneously detect built-up regions from them. Generally speaking, 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, in this section, I use the corner feature to infer the locations of potential built-up regions in the given images. Corner detection has been a longstanding problem in computer vision. In order to achieve a reliable extraction of corners from built-up areas, we proposed two criteria, which take both Edge points and Corner response into consideration, to validate and filter a large set of initial extracted Harris corners.

A. Edge Points

A corner can be defined as the intersection of two edges. A corner can also be defined as a point for which there is two dominant and different edge directions in a local neighborhood of the point. An interest point is a point in an image which has a well-defined position and can be robustly detected. This means that an interest point can be a corner but it can also be, for example, an isolated point of local intensity maximum or minimum, line endings, or a point on a curve where the curvature is locally maximal. We should easily recognize the point by looking at intensity values within a small window shifting the window in any direction should yield a large change in appearance. The figure shows the edge points in the Edge Point Detector.

B. Corner response

It is the intersection of two edges, it represents a point in which the directions of these two edges change. Hence, the gradient of the image (in both directions) have a high variation, which can be used to detect it. Since corners represents a variation in the gradient in the image, we will look for this "variation". Consider a grayscale image. We are going to sweep a window (with displacements in the x direction and in the right direction) and will calculate the variation of intensity.

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

where: $w(x,y)$ is the window at position (x,y) , $I(x,y)$ is the intensity at (x,y) , $I(x+u,y+v)$ is the intensity at the moved window $(x+u,y+v)$ Since we are looking for windows with corners, we are looking for windows with a large variation in intensity. Hence, we have to maximize the equation above, specifically the term:

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

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C Thresholding Method

The output of the thresholding operation is a binary image whose gray level of 0 (black) will indicate a pixel belonging to a print, legend, drawing, or target and a gray level of 1 (white) will indicate the background. The main difficulties associated with thresholding such as in documents or NDT applications occur when the associated noise process is non-stationary, correlated and non-Gaussian. Other factors complicating thresholding operation are ambient illumination, variance of gray levels within the object and the background, inadequate contrast, object shape and size non-commensurate with the scene. Finally the lack of objective measures to assess the performance of thresholding algorithms is another handicap. In fact most authors limit themselves to the visual inspection of a few test cases. A document image analysis and recognition system includes several image processing techniques, beginning with digitization of the document and ending with character recognition and natural language processing

Thresholding is one of the first low-level image processing techniques used, before document analysis step, for obtaining a binary image from its gray scale one. The thresholding step can be quite critical in that it will affect the performance of successive steps such as segmentation of the document into text objects, and the correctness of the OCR (optical character recognition). Improper thresholding causes blotches, streaks, erasures on the document confounding segmentation and recognition tasks.

We categorize the thresholding methods in six groups according to the information they are exploiting. These categories are:

1. Histogram shape-based methods where the peaks, valleys and curvatures of the smoothed histogram are analyzed.
2. Clustering-based methods where the gray level samples are clustered in two parts as background and foreground (object) or alternately are modeled as two Gaussian distributions.
3. Entropy-based methods result in algorithms, for example, that use the entropy foreground-background regions, the cross-entropy between the original and binarized image etc.
4. Object attribute-based methods search a measure of similarity between the gray-level and binarized images, such as fuzzy similarity, shape, edges, number of objects etc.
5. The spatial methods use the probability mass function models taking into account correlation between pixels on a global scale.
6. Local methods do not determine a single value of threshold but adapt the threshold value depending upon the local image characteristics.

III CLASSIFICATION ON THE CANDIDATE BUILT-UP REGIONS

In each image in the input image collection, I repeat the aforementioned step to locate candidate urban regions.. Some non-built-up region may be wrongly extracted as well. Upon inspection, I find that most of the false-alarm samples are regions that contain many man-made objects inside them, like airport, harbor, etc. Moreover, since we utilize a binarization processing to extract candidate built-up regions, false alarms may be extracted from the image which does not contain any built-up regions.

However, from a set of extracted candidate building regions, I 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 the false alarms. With this motivation, we proposed an unsupervised grouping algorithm to automatically discover the frequently recurring texture patterns corresponding to built-up areas and further finish the task of built-up area detection. The assumption here is that the “positive” samples (i.e., the ones containing a built-up region) will all have similar features, whereas the “negative” samples are uncorrelated and thus can be modeled by a random mixture of features. Based on the assumption, the proposed unsupervised grouping algorithm consists of three steps: feature extraction, grouping in feature space, and detecting built-up region.

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Figure 1.Input Image

A. Feature Extraction of Candidate Built-Up Regions

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

- Step 1) Convoluting the panchromatic band of each candidate region R_i with a Gabor filter bank [11] at K scales and S orientations (in the experiment, we set $K = 4$ and $S = 6$) to generate filter responses.
- Step 2) The resultant filter responses are aggregated and clustered into textons using the k-means algorithm, which are further used to form a texton dictionary Ω .
- Step 3) 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 it in the dictionary.

B. Grouping Candidate Built-Up Regions Using Spectral Clustering

In this step, we use 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.

- a) Suppose that there are M built-up samples extracted from the input image collection in the first stage, and $H = \{h_1, h_2, \dots, h_M\}$ denotes their corresponding texture histogram. Here, A_{ij} is defined as follows:

$$S(r_i, r_j) = K\chi^2(h_i, h_j) \quad (3)$$

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where h_i and h_j denote the texture feature histograms extracted from the candidate regions R_i and R_j , respectively (they are defined in Section III-A). $K_{\chi^2}(\cdot, \cdot)$ represents a χ^2 kernel function for two histogram inputs: $K_{\chi^2}(x, y) = \exp(-1/2 \sum_i ((x_i - y_i)^2 / (x_i + y_i)))$, where i indexes the histogram bins.

- b) Define D to be the $M * M$ diagonal matrix with $D_{ii} = \sum_j A_{ij}$, and then, construct the normalized affinity matrix $L = D^{-1/2} A D^{-1/2}$.
- c) Find u_1, u_2, \dots, u_l , the l largest eigenvectors of L , and form the matrix $E = [u_1, \dots, u_l] \in R^{M * l}$ by stacking the l eigenvectors in columns.
- d) For $i = 1, 2, \dots, M$, let O_i be the vector corresponding to the i th row of E , and cluster them into l groups B_1, \dots, B_l , via the k -means clustering algorithm. Afterward, assign the original point h_i to cluster j if and only if the corresponding row i of E is assigned to cluster j , thus obtaining the final clusters C_1, \dots, C_l with $C_j = \{i | h_i \in B_j\}$.

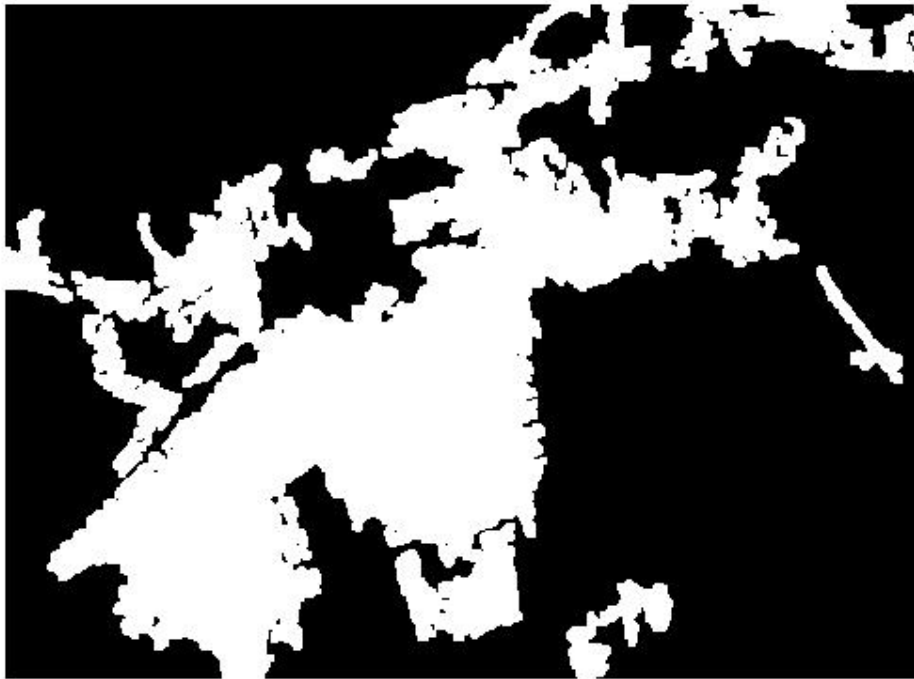


Figure2 corner response image

C. Detecting Built-Up Regions via Graph Cut

After grouping the candidate regions into several clusters, the final step is to identify which clusters are corresponding to the built-up region. Ideally, we 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

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several clusters. To handle this, we formulate the classification problem as a labeling problem, i.e., assigning each cluster C_i with a label $L(C_i)$ as follows:

$$L(C_i) = \begin{cases} 1, & \text{if } C_i \in \text{built-up region} \\ 0, & \text{if } C_i \in \text{non-built-up region.} \end{cases} \quad (4)$$

To express these desired properties of labeling, I define the cost function of labeling $E(L)$ as

$$E(L) = \sum_i V_d V_d(C_i, L(C_i)) + \sum_{i=j} V_s(C_i, C_j, L(C_i), L(C_j)) \quad (5)$$

where the data term measures the possibility of each cluster belonging to a built-up region, which is defined as

$$V_d(C_i, L(C_i)) = \begin{cases} 1 - N_{C_i}/M, & \text{if } L(C_i) = 1 \\ \frac{N_{C_i}}{M}, & \text{if } L(C_i) = 0 \end{cases} \quad (6)$$



Figure 3 output image using Global Thresholding method

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IV. EXPERIMENTS

A. Data Set Description

I demonstrate the performance of our method using 70 test images, which are composed of 32 satellite images (Ikonos and Quickbird images) and 38 aerial photographs downloaded from Google Earth. In the experiments, we use these images to construct three data sets.

- 1) The first data set contains 45 images with 1-m spatial resolution.
- 2) The second data set contains 50 images. Among them, there are 30 images with 1-m spatial resolution and 20 images with 0.61-m spatial resolution. 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) The third data set contains ten images. This data set is used to test the robustness of the proposed method when the number of the input images is small.

V. CONCLUSION

In this paper, I have doing an unsupervised framework toward simultaneously discovering built-up regions from multiple high-resolution satellite images. The proposed method includes two major steps: first a likelihood-function based approach to extract candidate built-up regions, in which an improved Harris operation is proposed, and second spectrum clustering- and graph-cut-based unsupervised clustering algorithm for the final built-up area detection. Based on the extensive tests, the proposed approach demonstrates the following main advantages over the previous works. First, it can simultaneously detect built-up regions from multiple images, and our experiment results show that the performance of built-up area detection can be further improved by exploring the cues drawn from multiple images. Second, the entire process is highly automatic and requires no human interaction.

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