Modeling Urbanization Using Spatial Building Patterns*

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Abstract

Automatic extraction of buildings and modeling of their spatial arrangements provide essential information for urban applications. This paper describes our work on modeling urbanization using spatial building patterns. Building detection is done using Bayesian classification of multi-spectral information. The individual buildings are used as textural primitives, and co-occurrence-based spatial domain features and Fourier spectrum-based frequency domain features are used to model their repetitiveness and periodicity at particular orientations. These features are used to classify neighborhoods as organized (regular) and unorganized (irregular). Experiments with high-resolution Ikonos imagery show that the proposed technique can be used for automatic segmentation of urban scenes and extraction of valuable information about urban growth.

1. Introduction

Increase in the spatial resolution of remotely sensed imagery has enabled new studies and, at the same time, has brought out new challenges for urban applications. Most of the previous work characterize urban areas using the density of buildings [4]. This characterization is important in urban monitoring and change detection studies as fast growing cities often face the problem of unorganized urban growth, even illegal expansion, that causes the destruction of green areas and has severe negative effects on the environment.

The complexity of urban scenes demands the development of new techniques because the traditional approach of pixel-based classification cannot model objects such as buildings and their structure in an urban setting. Alternative techniques model neighborhoods using histograms of texture elements to approximate spatial patterns [1], and properties of graphs of line segments for classification of scenes as rural, residential or urban [7].

Our work involves detection of individual buildings using multi-spectral information, and texture-based modeling of their spatial arrangements within image scenes. The individual buildings are used as textural primitives, and co-occurrence-based spatial domain features and Fourier spectrum-based frequency domain features are used to model their repetitiveness and periodicity at particular orientations. The spatial arrangements we are interested in correspond to regular patterns and irregular patterns that represent highly organized and unorganized neighborhoods, respectively, as shown in Figure 1. The former represent urban areas that undergo planned land development whereas the latter correspond to areas that are affected by unorganized and even potentially illegal expansion.

(a) Regular (organized) (b) Irregular (unorganized)

Figure 1: Examples of building patterns.

The rest of the paper is organized as follows. Section 2 discusses building detection. Section 3 presents the proposed approach for modeling building patterns. Section 4 describes the classification of image sub-windows using these models. Section 5 presents experiments using three Ikonos scenes of Ankara, Turkey. Finally, Section 6 provides a summary and indicates future research directions.

2. Building Detection

Techniques that are specifically designed for detection of buildings using their spectral, edge and shape properties can be found in the literature. Our goal in this paper is to evaluate measures of arrangements of buildings so we developed a simple detector for individual buildings. This detector uses a two-class Bayesian classifier trained on the pan-sharpened RGB bands of Ikonos images. Gaussian mixtures are used as the class-conditional distributions with 3

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components for the building class and 6 components for the non-building class.

To remove the false positives from the resulting binary map, first, we clean small noisy pixels using the morphological opening by reconstruction operation with a disk structuring element with diameter of 5 pixels. Then, we remove the connected components with an area smaller than 50 m^2 or greater than 6,000 m^2. These area thresholds were determined empirically by examining the sizes of the buildings and the false positives.

3. Modeling Building Patterns

Detection of building groups needs region-based analysis. However, segmentation techniques usually assume that regions consist of uniform feature distributions and cannot delineate areas that include several objects (buildings) and the background (trees, grass, roads, etc.). Therefore, dividing images into non-overlapping sub-windows and analyzing the individual sub-windows have been the common approach used for image partitioning [1, 7].

Texture has been acknowledged to be an important visual feature used to classify and recognize objects and scenes. It can be characterized by textural primitives as unit elements and neighborhoods in which the organization and relationships between the properties of these primitives are defined. However, an important problem has been the definition and detection of textural primitives. Thus, pixels are used as the unit elements and features are extracted for pixel neighborhoods. In this work, we use buildings as the unit primitives, and use spatial domain and frequency domain texture features for characterizing their spatial arrangements. Details of the features are described below.

3.1. Spatial domain periodicity analysis

Several comparative studies showed that features extracted from co-occurrence matrices are very effective features for texture analysis [8]. Co-occurrence, in general form, can be specified in a matrix of relative frequencies $P(i, j; d, \theta)$ with which two texture elements separated by distance d at orientation θ occur in the image, one with property i and the other with property j.

In order to use the information contained in co-occurrence matrices, Haralick *et al.* [3] defined 14 statistical features that measure textural characteristics such as homogeneity, contrast, organized structure, and complexity. Conners and Harlow [2] showed that the local minima of the contrast (inertia) feature among these 14 can be used to detect periodicity at a given orientation. Zucker and Terzopoulos [9] defined a χ^2 (chi-square) statistic to measure the amount of structure at a particular inter-pixel distance and orientation. Starovoitov *et al.* [6] compared 22 co-occurrence-based features for periodicity analysis, and concluded that seven of these features are useful for this purpose.

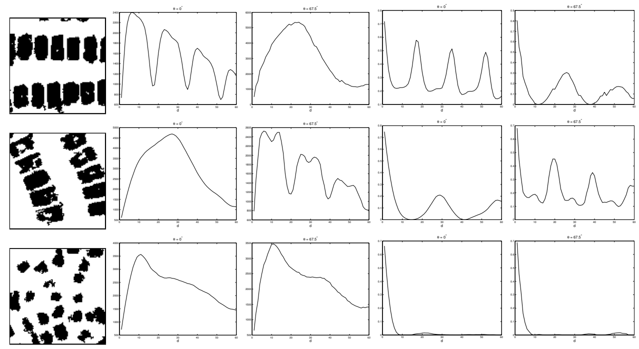

Figure 2: Example building patterns (first column), the contrast features for 0 and 67.5 degree orientations (second and third columns), and the χ^2 features for 0 and 67.5 degree orientations (fourth and fifth columns). The first two rows represent organized neighborhoods where the third row is an example of an almost random arrangement. x-axes in the feature plots represent inter-pixel distances of 1 to 60.

We use both contrast and χ^2 features to detect periodicity and directionality. Given a binary classification map where 1 represents buildings and 0 represents everything else, and the corresponding co-occurrence matrix computed at particular d and θ, the contrast feature [6] reduces to

$$x_i = P(0,1) + P(1,0) \quad (1)$$

and the χ^2 statistic [6] reduces to

$$y_i = \frac{(P(0,0)P(1,1) - P(0,1)P(1,0))^2}{a} \quad (2)$$

where $a = (P(0,0) + P(0,1)) \times (P(1,0) + P(1,1)) \times (P(0,1)+P(1,1))\times(P(0,0)+P(1,0))$. We compute these features at 1 to 60 inter-pixel distances and eight different orientations $i\frac{\pi}{8}$, $i = 0, \ldots, 7$.

Example building patterns and the corresponding features are given in Figure 2. These examples show that the features at a particular orientation exhibit a periodic structure as a function of distance if the neighborhood contains a regular arrangement of buildings along that direction. On the other hand, features are very similar for different orientations if there is no particular arrangement in the neighborhood. To extract a single feature vector, we sum the feature values along each orientation and obtain a feature vector of length 8 (one value for each direction). Vectors for contrast and χ^2 features are computed separately. Finally, values in these vectors are sorted to achieve rotation invariance.

3.2. Frequency domain periodicity analysis

It is well known that the radial distribution of values in the Fourier spectrum of an image (which is analogous to spatial autocorrelation [5]) is sensitive to texture coarseness in that image. It is also well known that the angular distribution of values in the spectrum is sensitive to the directionality of the texture in the image [8].

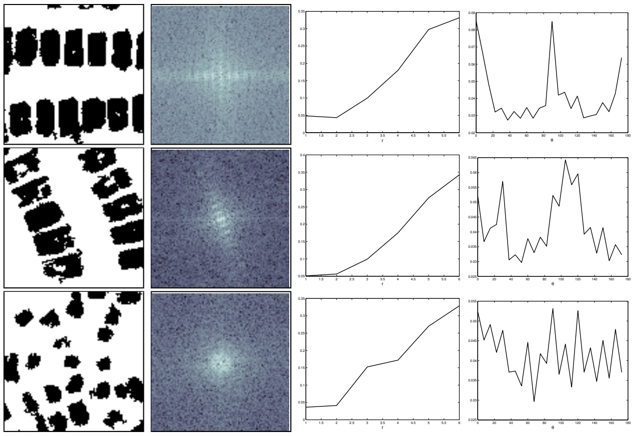

Figure 3: Example building patterns (first column), Fourier spectrum of these patterns (second column), and the corresponding ring- and wedge-based features (third and fourth columns). (Neighborhoods are described in Figure 2.) x-axes for the feature plots represent the rings and wedges.

Given the spectrum function $S(r, \theta)$ expressed in polar coordinates, features that capture texture periodicity and directionality can be computed by integrating (summing in the discrete case) S over ring-shaped and wedge-shaped regions centered at the origin, respectively. The ring-based (periodicity) features have the form

$$x_i = \sum_{r=r_i}^{r_{i+1}} \sum_{\theta=0}^{\pi} S(r, \theta) \tag{3}$$

where r_i and r_{i+1} are the inner and outer radii of the ring. We set r to powers of 2 (e.g., $[0, 2)$, $[2, 4)$, $[4, 8)$, etc.) as in [8]. The wedge-based (directional) features have the form

$$y_i = \sum_{\theta=\theta_i}^{\theta_{i+1}} \sum_{r=1}^{r_{\max}} S(r, \theta) \tag{4}$$

where θ_i and θ_{i+1} are the slope and $r_{\max}$ is the radius of the wedge. (The DC component is omitted since it is common to all wedges.) We set θ as $\theta_i = (2i - 1)\frac{\pi}{2n}$, $i = 0, \ldots, n$, where n is the number of wedges and is set to 24.

Example building patterns and the corresponding feature vectors are given in Figure 3. These examples show that the peaks in the features correspond to the periodicity and directionality of the buildings, whereas no dominant peaks can be found when there is no regular building pattern. Since we are interested only in the periodicity (i.e., organization) but not the directionality, the wedge-based feature vectors are circularly shifted so that the largest value is at the origin for rotation invariance.

4. Scene Classification

Given the multi-spectral image of a large scene, first, each pixel is classified as building or non-building using the classifier in Section 2. Then, the resulting classification map is partitioned into non-overlapping sub-windows of 100×100 pixels and textural features are computed for each sub-window as in Section 3. Finally, each sub-window is classified using binary decision tree classifiers trained by manual labeling of several sub-windows as regular (organized) or irregular (unorganized). Decision trees were chosen because they do not require any assumptions about neither the distributions nor the independence of features, and they also automatically perform feature selection.

Table 1: Confusion matrix for building detection (test data).

		Detected		Total	Accuracy (%)
		building	non-building		
True	building	73,518	6,163	79,681	92.26
	non-building	26,029	535,535	561,564	95.36
Total		99,547	541,698	641,245	94.98

5. Experiments

Three scenes ($4,000 \times 3,000$ pixels each) of pan-sharpened RGB bands of 1 m spatial resolution Ikonos images of Ankara, Turkey were used to evaluate the proposed features. Two separate sets of pixels were manually labeled to form independent training and testing data for evaluating building detection. After the buildings were detected, the scenes were divided into 100×100 sub-windows, and each sub-window was classified using the texture features.

5.1. Evaluation of building detection

Table 1 shows the performance of the Gaussian mixture-based building classifier on testing data where the error rate was obtained as 5.02% (error for the independent training data was 5.06%). Note that these rates were computed before applying morphological and area-based cleaning operators that further decrease the number of false positives. The error rates were quite low considering that only multi-spectral values were used for classification. Examples of detected buildings are shown in Figure 4.

5.2. Evaluation of scene classification

Example classification results are given in Figure 4. We performed classification using two spatial domain and two frequency domain feature sets, and the results were similar for different sets (since ground truth is limited, only qualitative results are given). Figure 4 presents only two cases due to space limitations. Visual evaluation of the results showed that most of the neighborhoods were classified correctly. Errors were mostly caused by different densities of buildings in different neighborhoods. In particular, some neighborhoods were incorrectly classified as unorganized when they contained a low density of regularly placed buildings. Some errors were also due to sub-windows that were on the boundary between organized and unorganized neighborhoods. The overall evaluation of the three scenes

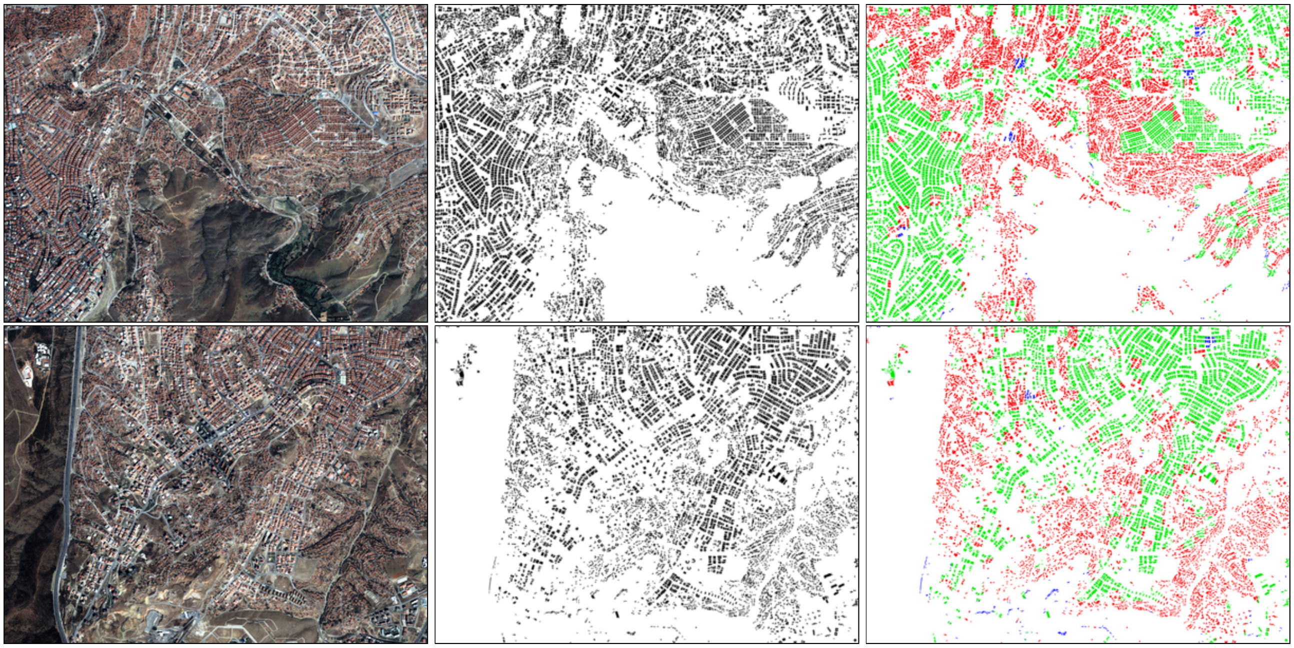

Figure 4: Example classification results for two $4,000 \times 3,000$ Ikonos scenes. The left, middle and right columns show the original data, the detected buildings, and the neighborhoods classified using the χ^2-based spatial domain features, respectively. Buildings (connected components) belonging to neighborhoods classified as organized are shown as green, buildings in unorganized neighborhoods are shown in red, and buildings that could not be classified to either type are shown in blue.

showed that the texture features can capture spatial building patterns and can model urbanization in most of the cases.

6. Summary

We described a new method for analyzing land development in high-resolution satellite imagery in terms of spatial arrangements of buildings. Spatial domain (co-occurrence based) and frequency domain (Fourier spectrum based) texture features were used to quantify the building patterns and classify neighborhoods as organized (regular) and unorganized (irregular).

We believe that segmentation of scenes based on high-level content such as the spatial patterns described in this paper will provide a significant contribution toward automatic semantic analysis of remote sensing image data sets, and will enable new results in urban planning, development and monitoring, and change detection studies. Future work includes using additional features for improving building detection, combination of different texture features for periodicity analysis, automatic selection of sub-window sizes for different neighborhoods, and application of spatial patterns to detect other periodic structures.

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