Unsupervised Delineation of Urban Structure Types Using High Resolution RGB Imagery

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Abstract

We present a method for delineating Urban Structure types (USTs) using only high resolution RGB image. As the method is unsupervised, it does not require training; the interpretations of delineated USTs are assigned a posteriori. The method utilizes freely available software and performs delineation in a short time even for very large images. A 1-meter resolution image of the entire Los Angeles is delineated as an example. We have found seven distinct UTSs which were given interpretations based on examination of their patterns. These interpretations are validated by population statistics. The method is aimed at broadening usage of USTs delineations for applications in urban and social studies.

1. Introduction

Urban structure types (USTs) are distinct spatial patterns of the urban structure at the neighborhood scale, which can be interpreted in terms of the type of activity or of residential pattern. Classification of a city into USTs complements standard land cover/land use classification by working at the scale that is significantly coarser than an individual pixel. Fairly extensive literature exists on how to delineate USTs from remotely sensed data (for example, see Heiden et al. 2012), but, because these works focus on supporting an effective urban planning, they use multisource data and supervised learning. It means that they are restricted to few places where such data exists and where the significant cost of supervised analysis is justified by the need. There also exists an extensive literature on using a single-source data (RGB or multispectral image) but only in the context of separating two specific types of USTs – formal from informal (slums) settlements; for example see Graesser *et al.* 2012. Proposed algorithms are restricted to this single purpose; they also are predominantly based on supervised learning.

In this paper we present an approach to delineation of USTs that uses only RGB images (many of which are freely available online) as an input, delineates an exhaustive set of USTs, is based on training-free, data-driven unsupervised principle, and can process very large input data in a reasonable time. In addition, our method relies only on existing public domain software. Our motivation is to make delineation of USTs more broadly accessible to analysts from different disciplines. The methodology is described and applied to a ~2 billion pixels 1m-resolution image covering the greater Los Angeles area.

2. Methodology

Our method is based on the concept of Complex Object-Based Image Analysis (COBIA) (Vatsavai 2013, Stepinski *et al*. 2015). In COBIA a raster (not restricted to an image) is divided arbitrarily into a grid of local blocks of cells. We refer to these blocks as motifels – they encapsulate a local pattern (motif) of raster variable. Motifels are much larger than pixels but they are also much more complex; motifels are used as elementary units for further analysis. COBIA is a well-suited approach to the problem of delineation of USTs from an RGB image. Individual pixels in the RGB image may not have an unambiguous interpretation, but we expect that the composition and arrangement of different colors within a motifel can be associated unambiguously with the specific UST. We utilize the GeoPAT toolbox (Jasiewicz *et al*. 2015) – open source collection of GRASS-GIS modules for pattern-based geoprocessing – to implement COBIA. GeoPAT works with categorical rasters, thus, as the preprocessing step, we first quantize an RGB image to obtain raster of color class labels.

We encapsulate the complexity of motifel structure by a color co-occurrence histogram and we calculate a degree of dissimilarity between two motifels using the Jensen-Shannon divergence (JSD) between their corresponding histograms. A grid of motifels, having dimensions much smaller than an original image, is first segmented into local areas of homogeneous patterns. Segmentation provides enhanced spatial cohesion to the final UST classification and reduces dimensionality of the subsequent clustering step. As spatially distinct segments may have very similar patterns, in the final step we cluster the segments into a small number of USTs. Both segmentation and clustering steps utilize JSD as the measure of distance. We use the segmentation algorithm which is custom-designed for grids of motifels. This algorithm is a part of the GeoPAT toolbox and is described in Jasiewicz *et al.*, (2016, this conference); its only parameter is the motifel's size. We use R implementation of the partitioning around medoids (PAM) algorithm to cluster the segments.

3. Delineating USTs in the Los Angeles area

To demonstrate our methodology we delineated USTs in the greater Los Angeles area (see inset in panel A of Fig.1) using 1-meter resolution RGB aerial imagery freely distributed by the U.S. Geological Survey (http://viewer.nationalmap.gov/launch). We downloaded 36 individual images from USGS and mosaiced them into a single image (shown in Fig.1 panel A) having dimensions of 41600×50200 pixels. This image was quantized into 27 color class labels to prepare it for GeoPAT processing. Next, we have chosen the size of the motifel to be 200 pixels (meters) which roughly corresponds to the size of the city block. With such a choice the image was transformed into a grid of 208×251 motifels. The segmentation step resulted in 4841 segments which were clustered into 7 USTs. The number of USTs was determined experimentally so the homogeneities of patterns in USTs are maximized while the number of USTs is kept to the minimum.

Because our method is unsupervised, an interpretation of each UST must be made a posteriori. To arrive to an interpretation we constructed a synthetic image for each UST. A syntetic image of an UST consists of 400 motifels selected randomly from its extent and organized into 20×20 array. Smaller versions of synthetic images for all USTs are shown in the last two rows in Fig.1. Based on examination of synthetic images we gave the USTs interpretations as listed in the legend in Fig.1. Two of the USTs (labeled as 5 – green areas and 6 – forest/shrub) are interpreted as undeveloped and uninhabited areas. Two other (labeled as 1 – sparse residential and 2 – dense residential) are interpreted as residential areas with detached housing. Two UST classes (labeled as 3 – dense urban and 4 – commercial/ind) are characterized by high percentages of impervious surface with the class 3 appearing to be a mixture of multi-level apartments, shopping centers, and urban infrastructure while the class 4 appears to contain only purely commercial structures. The seventh UST class (labeled as 7 – others) consists of large construction areas, barren land, and partially, of sparsely populated barren land.

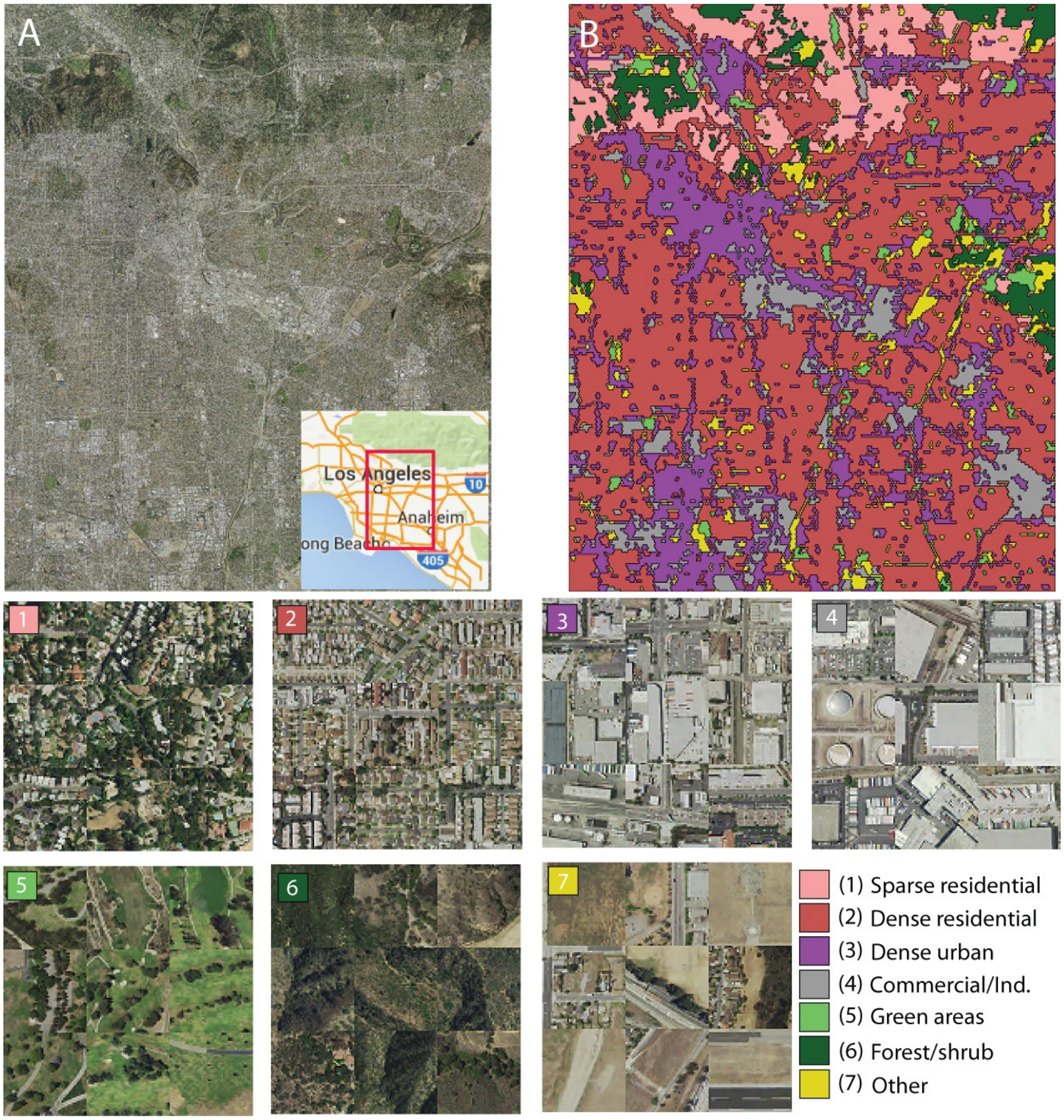

Figure 1: Unsupervised delineation of USTs in the Los Angele area. (A) Original 1-meter resolution image (inset shows the location of an image). (B) Map of seven USTs found in this area. The two lowest rows show a series of seven synthetic images each consisting of 9 randomly selected motifels from each UST. The legend to USTs is given in the lower right corner.

In order to validate our interpretations we used the newly available online resource SocScape (available at http://sil.uc.edu/webapps/socscape_usa/) which provides high resolution (30-meters) gridded population data over the entire US. Unlike the Census data, which gives population counts aggregated to areal units, SocScape data distinguishes between inhabited and uninhabited areas and can be used to calculate population density and the percentage of inhabited area in each UST class. The results are given in Table 1 and they confirm our interpretations.

Table 1. Population statistics for the UST classes

	1	2	3	4	5	6	7
Population density (people per ha)	20.0	50.2	40.3	8.9	2.9	0.6	10.8
% inhabited area	82.4	86.3	55.2	22.3	10.3	14.2	35.4

4. Conclusions

We presented a method for fast, unsupervised delineation of USTs from high resolution RGB images. We also demonstrated how this method works using an image of Los Angeles area as an example. For this large image the processing time on the 8-core I7 computer was ~30 min of which ~20 min was color quantization preprocessing. The results indicate that the method gives reasonable and valuable results using only easy-to-obtain RGB image and our software which is in the public domain. This is in contrast to other works on delineation of USTs which either use multisource, difficult to get data or concentrate on an extraction of a single UST (slums), in both cases using proprietary software. We noticed that some USTs are more difficult to distinguish from the RGB image than others when using our method. In particular, dense urban environment mixes with some (but not all) infrastructure and light commercial environment (class 3). Increasing the number of clusters does not help to resolve this problem because these environments are indeed characterized by similar patterns in an image. As 1-meter RGB images are available from the USGS for the entire US, our method can be used for comparative studies among major US metropolitan areas. While combined with racial diversity grids from SocScape, an attempt could be made to link urban structure types to predominant racial compositions of various US neighborhoods.

Acknowledgements

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References

Graesser, J., Cheriyadat, A., Vatsavai, R.R., Chandola, V., Long, J., Bright, E., 2012. Image Based Characterization of Formal and Informal Neighborhoods in an Urban Landscape. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* 5(4), pp. 1164–1176

Heiden, U., Heldens, W., Roessner, S., Segl, K., Esch, T., Mueller, A., 2012. Urban structure type characterization using hyperspectral remote sensing and height information. *Landscape and Urban Planning*. 105, pp. 361–375

Jasiewicz, J., Netzel, P. & Stepinski, T., 2015. GeoPAT: A toolbox for pattern-based information retrieval from large geospatial databases. *Computers & Geosciences*, 80, pp.62–73.

Stepinski, T.F., Niesterowicz, J. & Jasiewicz, J., 2015. Pattern-based Regionalization of Large Geospatial Datasets Using Complex Object-based Image Analysis. *Procedia Computer Science*, 51, pp.2168–2177.

Vatsavai, R.R., 2013. Object based image classification: state of the art and computational challenges. In *Proceedings of the 2nd ACM SIGSPATIAL International Workshop on Analytics for Big Geospatial Data*. pp. 73–80.