Urban structure types as a fingerprints of past, present and future city development

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Abstract

In this paper, we present an analysis of urban landscapes as a key to finding fingerprints of city structure. We segment a high-resolution data into natural areas with quasi-stationary spatial pattern and identify them as Urban Structure Types through unsupervised classification. In the last step, we use multi-dimensional scaling to analyse spatial and information relationship between USTs to identify the past, present and possible future trends in city development. Our case study was presented on the example of Poznań City as a typical lowland City in Central Europe.

Keywords: Urban landscape, City development, pattern-based segmentation, affinity propagation

1 Introduction

Urban landscape and its change provide an insight into the history and possible trends of future changes (Ramachandra et al., 2012). Delimitation and classification into more general units is a step towards an effective urban planning and management. Urban structure types (USTs) are units at the very local scale – usually a city block (Heiden et al., 2012) and can be interpreted in terms of residential pattern or ecological situation. In the past, USTs were delineated manually (EU Urban Atlas), but in the last years, an advantage of remote sensing techniques and the growing availability of high-resolution data have shifted entire process to automated procedures. Current methods rally on multi-spectral images (Hofer et al., 2009) but still require multiple spatial indicators and texture measures (Wurm et al., 2009; Heiden et al., 2012). In existing methods, USTs are determined by supervised learning (Graesser et al., 2012) or *a priori* knowledge in the form of rule system which means that all possible UTSs are limited to a pre-defined set and charged by researcher knowledge. Recently Niesterowicz et al. (2016a) shown a successful unsupervised approach to recognition of USTs directly from RGB images based on the concept of Complex Object-Based Image Analysis (COBIA) (Vatsavai, 2013; Stepinski et al., 2015).

In this paper we concentrate on unsupervised, rule- and training-free, data-driven process which aims to delineate natural UST where classification is added *a posteriori* without any prior restrictions or assumptions. Such approach is not charged by existing knowledge of researchers and gives

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better insight into the complete structure of the city, also allows to investigate internal relations between detected USTs in the context of past, present, and future city development. As an input we use a high-resolution urban land-cover map (HRLC-map) and as an output more general map of Urban Structure Types(UST-map). As a demonstration area we have chosen a city of Poznań (western Poland) presented in a form of a thirteen categories map of size 22000×21000 cells and 1m resolution. Poznań was selected because of its lowland city, with centric structure and without any natural constraints. The map was developed using LIDAR cloud supplemented by OpenStreetMap (OSM). The HRLC-map map was then segmented using GeoPAT (Jasiewicz et al., 2015) and segments have been clustered using an affinity propagation algorithm (Frey and Dueck, 2007). All clusters have been labelled and its spatial distribution over the city has been used to identify different zones of city development.

2 Data and Methods

The data processing routine is shown in Figure 1 and involves three steps: a compilation of the high-resolution map and its verification; segmentation into segments containing unique quasi-stationary patterns and segment clustering and labelling. Segmentation and clustering are data-driven and our impact on that process was limited to the selection of few parameters which roughly influence the final amount of segments and clusters.

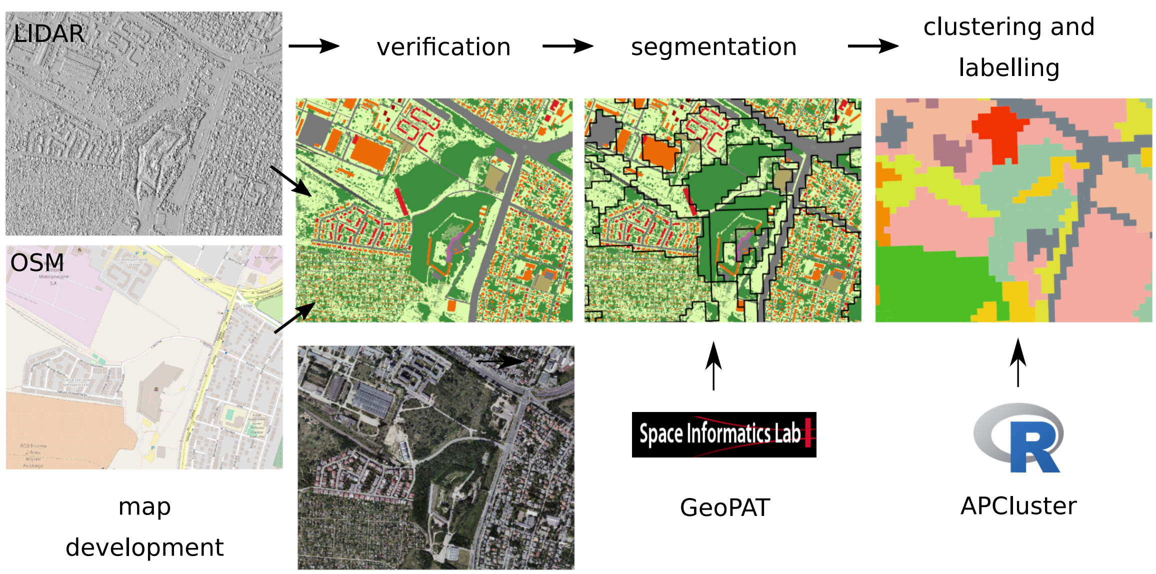

Figure 1: A data processing routine. From LIDAR cloud to Urban Structure Types

2.1 High resolution urban land cover map

As a basis for the high-resolution map, we used a LIDAR cloud. This is because remotely sensed imagery often results in confusion in complex urban systems (Lu et al., 2010). LIDAR data became more and more accessible and provides more direct information than multi-spectral images like for example types of vegetation and buildings heights. The original cloud has been acquired in 2012 (the latest available) with scan density $12 points/m^2$. This scan density was sufficient to correctly acquire all buildings bigger than $2m \times 2m$ and to calculate their height as a difference between the surface (upper) and terrain (lowest) elevation. Such minimal size was required to acquire regular buildings, informal developments, and other permanent facilities. In addition to the buildings and constructions, high-density LIDAR scan provides detail information about vegetations that fills the urban space as a factor. LIDAR attributes allow distinguishing between different type of green areas including lawns, shrubs and even single trees. Information about roads has been extracted from OSM supplemented by LIDAR reflection intensity attribute. The final map consists of thirteen classes presented at the Figure 2 and was verified on the basis of Orthophoto map acquired at the same time span. The purpose of verification was primarily to check the quality of the detection of small buildings across allotment gardens and the type of surface (hard/soft) on squares and car park areas.

Figure 2: A) Fragment of HRLC-map used as an input for segmentation; B) UST-map as result of segmentation and further clustering. Black border marks administrative City limits

2.2 Segmentation and clustering

In the last years, we proposed (Jasiewicz et al., 2015; Stepinski et al., 2015; Niesterowicz et al., 2016b), a new technique of delineation of very large categorical rasters in reasonable time referred as COBIA (Vatsavai, 2013; Stepinski et al., 2015). With this technique an entire raster is divided arbitrarily into a regular grid of local blocks containing local motifs of raster variable (here: land cover classes) called *motifels*. The only representation of motifel is its signature and the only possible operation is a calculation of distance/similarity between two or more motifels. An internal complexity of the motifel is encapsulated in its complex histogram. Recently we developed a new segmentation algorithm (Jasiewicz et al., 2016)[1], which has several advantages: it adopts segmentation criteria to local complexity, uses seeded and hierarchical region growing and maximises segments homogeneity by post-growing re-ordering. We also proposed a new signature which represents complex structure of motifels as a set of histograms each representing nested level of motifel decomposition (Remmel and Csillag, 2006). To calculate dissimilarity between motifels we use s newly proposed triangular measure, which shows high degree of compliance with Jensen-Shannon Similarity (Connor, 2016), but is much more simple and an order of magnitude faster.

$$d_{tri}(P,Q) = \sqrt{\frac{1}{2}\sum\frac{(P_i - Q_i)^2}{P_i + Q_i}} \qquad \text{Equation 1}$$

During segmentation we set only two parameters: size of motifel (we used $32x32$ cells) and minimal area which was set to 5 motifels. segmentation finished with 7346 segments which has been clustered into 20 structure types using an affinity propagation algorithm (Frey and Dueck, 2007) implemented in R with preference parameter set to -2 and similarity matrix consistently calculated with the triangular measure. Consequently, we have received 20 classes which have been subject to further interpretation. Label's assignment was manually checked on 200 randomly selected segments, and we found that in no more than 15% the assignment was not consistent with the best human's choice.

3 Discussion and conclusions

Unsupervised, pattern-based analysis allows to delineate, identify and classify urban structure types as well as to investigate a relationship between them, both in information and geographic space. The relation between clusters is shown in Figure 3A in the form of a multi-dimensional scaling diagram (Sammon's map) where the two-dimensional distance between objects approximates the multi-dimensional distance in information space. This diagram shows internal order: structures dominated by one land cover class (USTs: 14,15,19,20, see Fig. 2) arrange at its perimeter due to low similarity to any other UST except itself. Those UST with more compound internal structure are arranged by two factors: a degree of filling up of space (both buildings and vegetation) and degree of built-up. This observation allows to distinguish two groups of developments:

*Areas already developed*include areas where space is completely or almost completely filled with buildings and/or trees. It covers densely built-up city centres (1), multi-family estates developed in the second half of the 20th century (3) and a few types of single-family detached developments originating also from the seventies to the eighties of the twentieth century, usually built by own effort of owners. This group also contains allotments gardens (11), a popular form of amateur farming developing on the outskirts of the cities.

*Areas under development and future development*include areas where space is partially built-up or not filled at all and with a small amount of high vegetation. New developments appear at former

[1] Also submitted to Computers and Geosciences

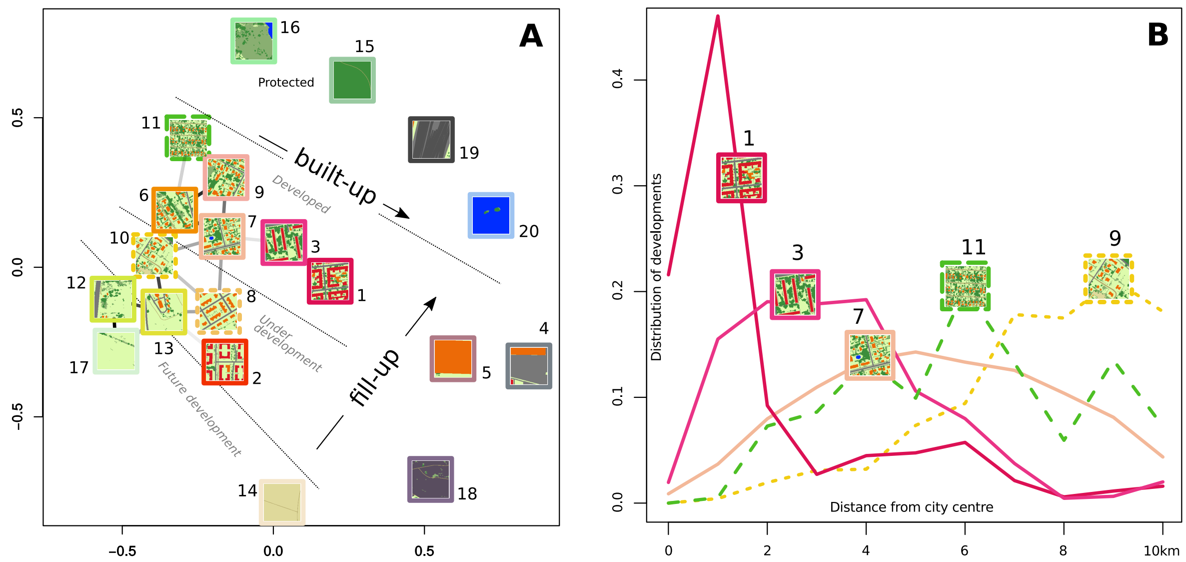

Figure 3: A) Average distance between all twenty classes - results of AP- clustering. Numbers correspond to labels presented in Fig. 2B; B) Distribution of the distance from the city centre of five selected classes

arable lands or open spaces and high vegetation requires several years to grow between buildings. This group covers new multi-family estates (2) with a little bit different spatial pattern than those from the twentieth century and new single-family development both individually with an irregular arrangement of buildings (10) as well as those built by developers with a more regular pattern (8). A future-development group covers mostly open spaces with little development (13,18) or undeveloped (17) and arable lands (14) outside the city.

A spatial distribution of selected USTs is presented in Figure 3B and show a regular and typical structure of centric cities. The city centre built-up type covers area in a 1.5-2km radius from the city centre, multi-family estates have their highest frequency from outside the central zone up to a 4 km limits where individual development gains its maximum. A mutable distribution of allotments illustrates the process of city spreading during the twentieth century, while emerging developments built after 2000 are concentrated at the edge of the built-up area and illustrate the continuing process of city sprawl (Batty et al., 1999) and fill up gaps in between existing developments.

Acknowledgements

This work was supported by the National Science Centre (NCN) Grant DEC-2012/07/B/ST6/01206 and NASA Project NNX15AJ47G. We also thanks to anonymous reviewer for his/her helpful comments and language improvements.

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