Identification of urban structures on regular squared grids with the help of spatial calculus

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Technological innovation: Identification of urban structures on regular squared grids with the help of spatial calculus

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Abstract

Pixel classification into landscape categories is a common task since the development of remote sensing. Many approaches such as Markov field classification are often used, and enable to create urban atlases. However, these techniques are not adequate to analyse urban structures at the city scale, as they are local. This paper presents a post-processing method to transform labelled pixels into urban structures. The method identifies urban 'morphotypes' that are assembled into urban structures. Then the graphical language of 'chorems' is used to represent the structures graphically.

Keywords: image classification, spatial calculus, urban structures, chorems

1. Introduction

While cities are indeed complex systems, the issue of delimiting the perimeters of these systems is rarely tackled. Indeed, the analyses often rely on administrative definitions of the city on which statistical systems provide data. However, as far as sustainability is concerned, the most critical parts of today's cities are generally the fringes of agglomerations, where natural space consumption is high, and car use and energy consumptions are uncontrolled. These hinterlands are badly described by statistical systems because they overlap administrative boundaries. To overcome this problem, European institute for statistic studies now publish gridded population data.

These gridded population data enable to apply remote sensing algorithms to classify them. Indeed, after the characterisation of each cell of the grid with several indicators computed from population density and analysis of buildings, the data set is quite similar to a multivariate image (excepted for the normalisation of pixel ranges).

There exist many approaches to classify multivariate images into similar areas, such as Markovian classifiers [1,2]. Typically, a semi-supervised classification performed on the cells of the image enables to label groups of pixels as urban categories such as dense centre, dense suburb, individual housing area, commercial and industrial areas, etc. Almost all classifiers take into account local neighbourhoods but not the global structure of the agglomeration [3].

The method presented in this paper transforms these urban spots into urban structures by relabeling the cells into categories related to urban phenomena: historical centre, first outer ring, inner suburb, connected secondary centre, etc. with the help of a qualitative spatial calculus. The categories related to urban phenomena are called 'morphotypes'. They have larger extents than the urban spots obtained by image classification, and have a higher semantics. The composition of morphotypes creates urban structures whose parts are spatially organised and can be graphically represented in the spatial modelling language of 'chorems'.

2. Supervised pixel classification of population and built area

2.1 Data

The gridded census data published by INSEE are on a regular squared grid with a pixel size of 200 m. As urban fabrics can be characterised by built density as well as by population density, two other indicators are added here to the size of the population: the size of the built area, and the entropy of this built area (Fig. 1).

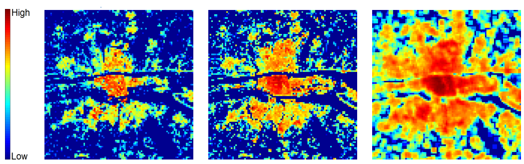

Fig 1. Data used for classification: population (left), built area (middle), entropy of built area (right). Source: INSEE and IGN (2013). Author: J. Baro

2.2 Supervised classification with Markov field algorithm

A Markov field classifier from the family of Hidden Markov Random Fields [4] is used to label the pixel of the dataset as urban spots. Several Markovian models have been estimated on several cities of different sizes, and the models are transferred to the area of study with an algorithm adapted from [5].

The urban spots identified by the classifier belong to six classes that can easily be interpreted as typical urban classes: historical centres, collective housings, mixed housings, individual housings, dense and sparse individual housings and activity centres. Naturally, given the data used in the classifier, all classes relate to the density of inhabitants and of build areas. Fig. 2 presents the results of the classification for the agglomeration of Besançon (France), ca. 200,000 inhabitants.

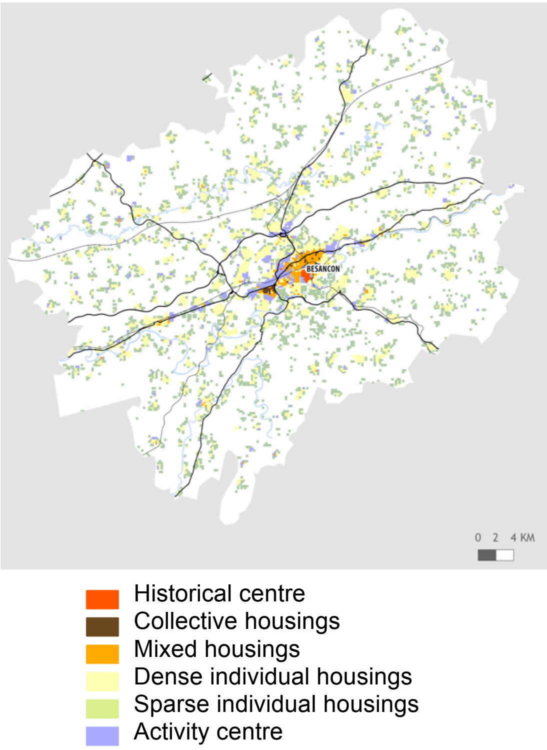

Fig 2. Urban spots of Besançon (France) obtained by the urban classifier. Data: INSEE and IGN (2013). Author: J. Baro.

The use of neighbourhoods in the classifier enables to find the boundaries of each urban spot but does not reveal the spatial organisation of these urban spots. The density gradient between the city centre, collective housings and individual housings is clearly present in the map of Fig. 2, but not explicitly represented. The only high-level structure that has been characterized is the city centre because it generally has a clear signature of population and built density.

3. Identification of urban structures

The map obtained by the classifiers does not contain some of the semantics classically attached to cities. The hierarchical organisation of city centres into primate and secondary centres, as well as the presence of other urban cores in the metropolitan area is impossible to detect without analysing the data at the global scale. In a raw classification, housing areas are not explicitly organised into patterns such as concentric rings or patches along the roads.

While the classification task is mostly inductive, the identification of urban structures is partly deductive. The structures come from an *a priori* knowledge of the expected organisation of urban areas, either from the literature or from observation.

3.1 Spatial primitives

The first structure that must be analysed is the density gradient from the city centre to the fringes, typical of the Von Thünen model [6] that can be extended to the case of several centres. This structure is quite informative because it relates to urban growth and is often considered to be the classical shape of cities. However, it does not take into account the way industry, roads and railways shape the city and add some distortion to space.

The second structure relates to the specialisation of space. The sectorial model of space by Hoyt [7,8] is typical of the persistence of a Central Business District and of a gradient of density, mixed with space specialisation, resulting in radial sectors.

The third structure describes the organisation of urban cores and urban functions, with the concepts of urban hierarchy and of accessibility and market places in a similar way to the Christallerian approach.

These three axes of analysis are summarised into six typical spatial primitives created to describe graphically the urban structures to be detected (Fig. 3).

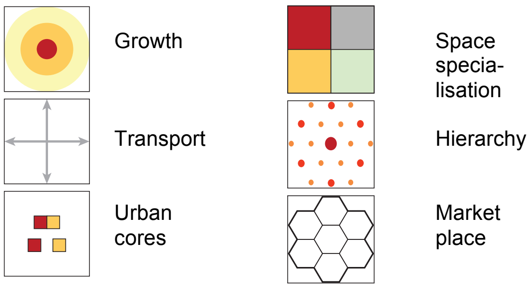

Fig 3. Urban structures to be identified. Author: J. Baro.

The detection of these urban structures cannot rely directly on the urban spots of Fig. 2. Indeed, the semantics of the urban spots is too weak, and the shapes of the spatial regions are too complicated. The approach to detect these urban structures is first to create 'morphotypes', and then to interpret the morphotypes with the small set of elementary urban structures from Fig. 3.

3.2 Region simplification

The first step to create the morphotypes is to suppress isolated pixels that do not bear useful information, and to simplify the boundaries of urban spots. This task is performed with simple decision trees on the sizes and on the neighbourhoods of urban spots, the latter being characterised by topological analysis.

At the pixel scale, all scattered housings are suppressed, and all historical centres with less than five neighbours in the same class are relabelled into the dominant label in the vicinity, to ensure that historical centres are compact enough. Collective housings are processed similarly.

At the region scale, small activity areas and small collective or mixed housing areas are either suppressed when they are isolated, or reclassified according to their neighbourhood. Indeed, very small activity areas or collective housing areas might be the result of classification errors, or too small to shape significantly the agglomeration. Again, the analysis of the neighbourhood enables to distinguish between noise and significant information.

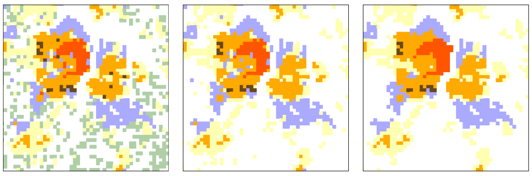

Fig 4. Region simplification: urban spots (left), after pixel simplification (middle) and after region simplification (right). The legend is the same as the one of Fig. 1. Author: J. Baro.

Fig. 4 illustrates the results of pixel and region simplification on the city of Lorient (France). The most drastic effect if the simplification at the pixel scale that enables the suppression of sparse individual housing as well as the simplification of the collective and mixed housing regions. The effect of the simplification at the region scale results in the removal of dense individual housing inclusions in the first ring of the city.

3.3 From urban spots to morphotypes

The final identification of morphotypes makes extensive use of the region connection calculus [9]. Identifying the morphotypes in this approach requires using qualitative spatial reasoning.

Some agglomerations can be considered to be the coalescence of several regions, identifiable by the relatively weak welding joint between these regions that generally occurs along transport infrastructures. To detect such a process requires distinguishing correctly between two operators of the region connection calculus, namely 'exteriorly connects' and 'partially overlaps'. With the 'opening' operator of mathematical morphology [10] applied to the binary image of individual housings, it is possible determine where are located the actual urban fringes. These urban fringes will be used in the remaining steps of the classification.

The morphotypes considered here are the primitive types that compose the urban structures of Fig. 3. The five urban spot categories (we have already discarded the sixth category of sparse individual housing) as well as the newly detected urban fringes are sub-classified into new categories according to characteristics determined by the region connection calculus and absolute or relative thresholds on their characteristics.

The historical centres are split into primate and secondary centres according to their relative surface in the agglomeration: the size of the primate centre must be greater than a third of the total surface of historical centres.

The collective and mixed housing areas are classified into either dense (or sparse, according to density) rings if they are connected to the primate and secondary centres, or tertiary centres if they are not connected to other centres.

The urban fringes are kept as urban fringes, or classified as connection zones if they are at the frontier between two coalescent urban systems.

Individual housing areas are also classified further into connected urban cores, relay urban cores, satellite urban cores or isolated urban cores according to their neighbourhoods. A connected urban core will have in its neighbourhood a primate, secondary or tertiary centre. A relay urban core will be connected to an urban fringe. An urban core inside a centre will be a satellite urban core. The remaining areas will be isolated urban cores.

Last, activity areas will be qualified of inner or outer activity areas according to their relative position with respect to city centres and dense rings.

The identification of morphotypes for the agglomeration of Besançon is represented on Fig. 5. When compared to Fig. 2 that represents the urban spots, the morphotypes are more detailed, simpler, and reveal a spatial organisation coherent with the urban structures that are to be detected. The river Doubs and the mountains shape the agglomeration, leading to asymmetries. Nonetheless, the global gradient that can be attributed to urban growth is clearly visible, with dense rings around the historical city centres, and the urban cores inside the periurban area, either connected or relay cores, are well identified.

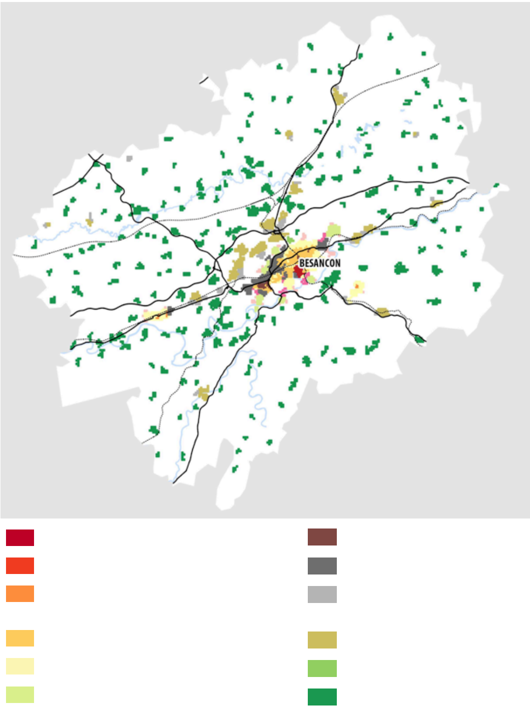

Fig 5. Morphotypes of Besançon obtained by qualitative spatial reasoning on the urban spots of Fig. 1. Author: J. Baro.

4. Representation of urban structures with a graphical modelling language: the chorems

The morphotypes identified with the help of qualitative spatial reasoning can be further organised by the use of a graphical modelling language.

A graphical modelling language is chosen here because the largest part of the information is to be found by comparing different areas of the agglomeration. While it is quite difficult to define what is a dense ring around a primate centre in general, the visual identification of such a ring is quite simple using the basis operations of analogy and comparison. To reveal further the spatial organisation of the morphotypes requires typifying the shapes to the point where the structure will become apparent.

Roger Brunet has introduced such a graphical modelling language for spatial information called ‘chorems’ [11]. Brunet’s approach is to focus on space organisation and to represent the spatiotemporal dimension of a phenomenon with the help of a graphical representation situated halfway between a map and a schema.

Chorems can be thought of as rules to graphically combine the morphotypes into schemata [12] describing explicitly the urban structures of Fig. 3.

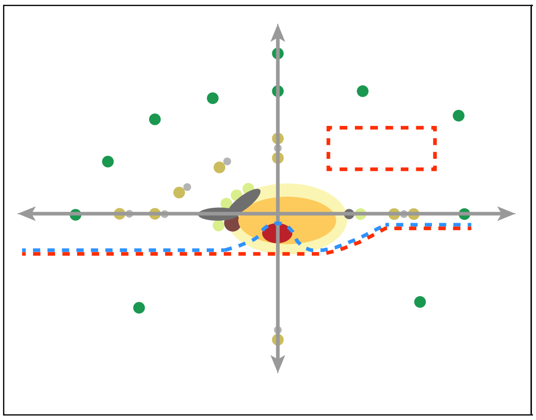

Fig 6. Chorematic representation of Besançon, with the same legend as the one of Fig. 5, the blue dashed line being a connector and the red dashed line being a separator. Author: J. Baro.

A chorematic representation of Besançon in the language of Fig. 3 is given in Fig. 6. Note that this representation is not a map, but a graphical layout of the concepts of centres, rings and cores that has been revealed in the morphotype analysis.

Besançon is clearly a city originally located along the river Doubs (blue dashed line) that has grown asymmetrically (because of the topography – red dashed lines) into a first ring of collective and mixed housing, and a second ring of typical suburbs with many individual housing. Two activity centres concentrate most of the activities on the fringes of this inner agglomeration. In the periurban area, a first ring of relay cores is composed of historical villages that have been attracted in the area of influence of the centre, and inhabited mostly by commuters. A second ring of independent villages can be found at a greater distance from the city centre.

This chorematic representation cannot be obtained automatically by a computer program yet. However the construction and analysis of morphotypes, obtained by image processing and qualitative spatial reasoning, contains all the necessary information to sketch the chorems.

5. Conclusion

This paper presents a new approach to graphically analyse and represent urban structures on the basis of pixel classifications such as those obtained by remote sensing or by the analysis of census gridded data. The originality of this work is to transform almost raw data with many pixels and too little semantics into more regular information that reveals pertinent urban concepts. The large amount of quantitative information handled in the urban classifications requires a qualitative approach: a spatial calculus. The identification of morphotypes is a good basis to analyse urban growth and the spatial organisation of urban structures. Last, the representation of these morphotypes with chorems enables to graphically model agglomerations and to reveal their structure.

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