Progressive Block Graying and Landmarks Enhancing as Intermediate Representations between Buildings and Urban Areas

Guillaume Touya, and Marion Dumont

Univ. Paris-Est, LASTIG COGIT, IGN, ENSG, F-94160 Saint-Mande, France; {firstname}.{lastname}@ign.fr

Abstract*:* Geovisualization applications that allow the navigation between maps at different scales while zooming in and out often provide no smooth transition between the individual building level of abstraction and the representation of whole urban areas as polygons. In order to reduce the cognitive load of the user, we seek to add intermediate zoom levels with intermediate and progressive abstractions between buildings and urban areas. This paper proposes a method based on progressive block graying while enhancing building landmarks, to derive these intermediate representations from the individual buildings. Block graying is based on an automatic building classification, and a multiple criteria decision technique to infer inner city blocks. The landmarks identification relies on machine learning and several criteria based on geometry and spatial relations. The method is tested with real cartographic data between the 1:25k (with individual buildings) and the 1:100k scale (with urban areas): transitions with one, two, or three intermediate representations are derived and tested.

Keywords: building generalization, landmarks, building classification, machine learning, multiple criteria decision

1. Introduction

Topographic maps are now more used in geovisualization applications, where they can be zoomed in and out, than on paper. However, the maps that are displayed in such applications are either derived from scanned paper maps independently generalized, or poorly generalized when directly produced for screens, and in both cases, the cognitive load of the user is quite significant, each time the scale changes. One of the causes for this cognitive load is the gap in abstraction in the representation of map objects: e.g. the buildings might be represented by individual polygons at one scale and by built-up areas at smaller scales (Dumont et al. 2016b). Even if most of traditional knowledge on how to make effective and beautiful maps still applies to these geovisualization applications, we do not know exactly what the best strategy is to generalize maps that enable a smooth navigation in such applications (Dumont et al. 2015). One strategy to smooth the navigation across scales is to use a varioscale model with continuous representations of map objects (van Oosterom et al. 2014). Another one is to add small number of consistent intermediate scales that gradually change the levels of abstraction and generalization (Dumont et al. 2015). This paper focuses on the latter strategy, as it is part of a broader research project that focuses on the derivation of intermediate scales. Comparing both strategies still is a future goal. The paper particularly deals with the specific abstraction gap between individual buildings that are often represented at scales around the 1:25k, and built-up areas represented at the 1:100k and smaller scales (Dumont et al. 2016b). What is the best strategy to gradually generalize the buildings into a built-up area to ease smooth zooming? The answer to this question can only be found by controlled usability tests (Šuba et al. 2016). For this we need some material to carry out the usability tests, i.e. map series from 1:25k to 1:100k that contain buildings that were differently generalized (Dumont et al. 2017). We identified three main strategies to generalize buildings at such scales: the classical agent-based generalization (Ruas and Plazanet 1996, Barrault et al. 2001, Duchêne et al. 2012) that enlarges and then contextually eliminates and displaces buildings; building typification (Sester 2001, Burghardt and Cecconi 2007); and the graying (or covering) of dense buildings blocks (Stoter et al. 2011). This paper proposes a generalization method that follows the latter strategy, by gradually graying building blocks while highlighting the building landmarks.

The following section briefly describes the type of map that we seek to achieve with the gradual block covering. Section 3 explains how blocks are ordered to be covered in the intermediate scales between individual buildings and built-up areas. Section 4 details how building landmarks are automatically extracted from the buildings. Section 5 shows some experiments where block covering and landmarks highlighting are jointly used to derive intermediate scales. Finally, Section 5 draws some conclusions and describes possible further research.

2. Gradual Block Covering

We define block covering or graying (because of the color used in the IGN maps to cover blocks) the operation that replaces individual buildings in a block by a polygon that covers the extent of the built-up area in the block. The block covering generalization strategy proposed in this paper stems from the 1:50k maps from Kadaster Netherlands. In these maps, the dense blocks are represented by a colored polygon that replaces the individual buildings, but individual buildings are kept where the density is low (Fig. 1). A similar strategy was proposed at Ordnance Survey, the British NMA (Regnauld and Revell 2007, Revell et al. 2011), with the amalgamation of buildings to create large polygons that cover the built-up area inside each block. As the aim of the project compare several generalization strategies to derive gradual intermediate scales in a multi-scales map, we selected the Kadaster approach for its simplicity and the fact that it abstracts more the building than the amalgamation approach.

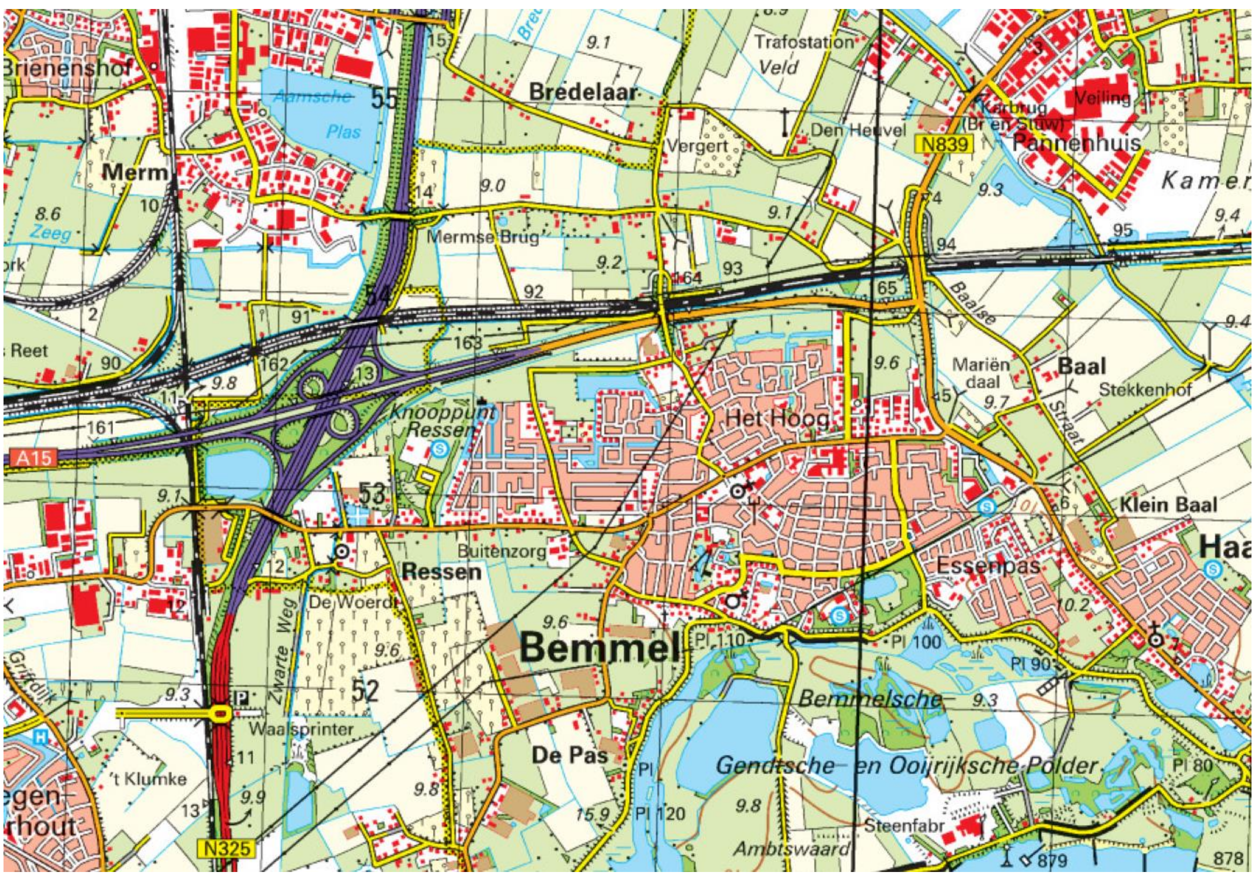

Fig. 1. Kadaster Netherlands 1:50k map extract: dense urban blocks are represented by colored areas, all buildings inside these blocks are removed (Stoter et al 2011).

This is a good intermediate abstraction between all individual buildings and only a built-up area, which could be even better by keeping the most important buildings in the dense blocks. To make this strategy gradual, we propose a three-step workflow (Fig. 2): inner city (very dense) blocks are identified to quickly cover them when zooming out of the 1:25k; buildings are classified to cover first urban and industrial buildings (i.e. the blocks that contain such buildings), and after suburban and rural buildings; landmarks are automatically inferred to keep them on the map even if their block is covered.

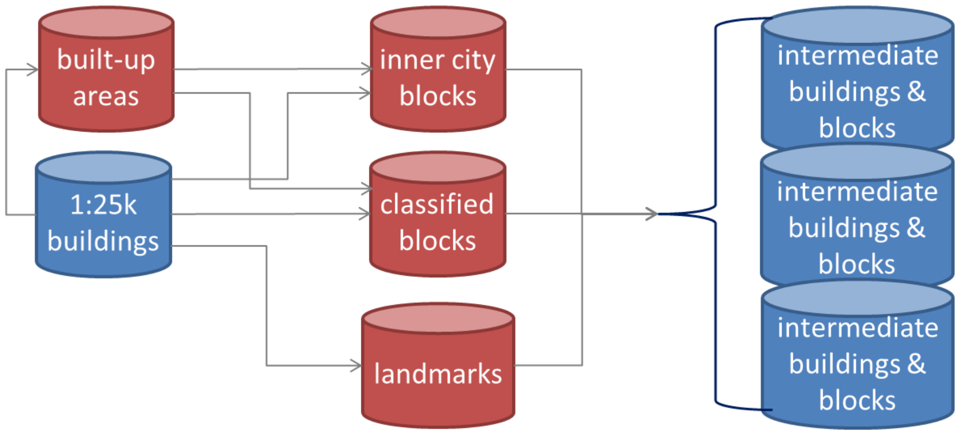

Fig. 2. Workflow for gradual block covering: the intermediate building layers are composed from inner city blocks detection, building classification and landmarks inference.

Towns are automatically derived from a buildings dilatation (Gaffuri and Trévisan 2003), while blocks are computed inside these towns using the faces of the road-river-railroad network graph.

3. Inner City Generalization and Block Classification

This section describes how building blocks are gradually covered using a multiple criteria decision technique to identify inner city blocks that should first be covered, and using a building/block classification to cover blocks at smaller intermediate scales.

3.1 Inner City Generalization

The inner city blocks considered here do not necessarily follow the common geographical characteristics of inner cities, as we are interested in the small, dense blocks, populated by large complex buildings that can be found in inner cities. Several criteria were derived from these general characteristics: (1) area, i.e. small blocks tend to be covered first as there is no space inside to enlarge the buildings; (2) density, i.e. the block area divided by the sum of areas of buildings and roads symbols, as too dense blocks cannot allow the display of its contained buildings once they are enlarged; (3) building area, i.e. the distribution of building areas inside the blocks, as very large buildings in a block leave no space for the other buildings of the block to be displayed. To aggregate these criteria in the decision of characterizing a block as inner city block to cover, we used the ELECTRE TRI multiple criteria decision technique, which was successfully used to infer the level of detail of OpenStreetMap by combining geometric and semantic criteria (Touya & Brando 2013). This technique does not aggregate the values for each criterion, because they are often hard to compare (how to compare an area to a density and to a distribution?), but makes order relations for each criterion (i.e. for this criterion, this block is more inner city than this one), and then aggregates the order relations: e.g. if all criteria give the same order relation, it is the global decision. This technique allows veto thresholds for criteria, i.e. the difference for a criterion is so important that the order relation derived from this criterion wins over the other criteria. Table 1 presents the criteria used in our method. Given the first results obtained with the first three criteria, two other criteria (centroid and neighborhood) were added with smallest weights to obtain more contiguous inner city blocks.

Table 1. Criteria used in the inner city detection algorithm

Criterion	Description	Weight	Veto threshold	Preference threshold
area	area of the block compared to the other blocks of the town	1.0	0.7	0.2
density	density of the block using buildings and road symbols	1.5	0.4	0.2
building area	area distribution of the inner building blocks compared to the distribution of building areas in the town	1.5	0.6	0.25
centroid	distance to town centroid	0.5	0.95	0.2
neighborhood	density of the neighbor blocks	0.8	0.4	0.3

Results obtained with the ELECTRE TRI method are presented in Fig. 3. The detected inner city blocks do not exactly correspond to the inner city space of the two cities, but match well with the inner city blocks that are too small and dense to preserve an individual building representation at scales smaller than 1:25k.

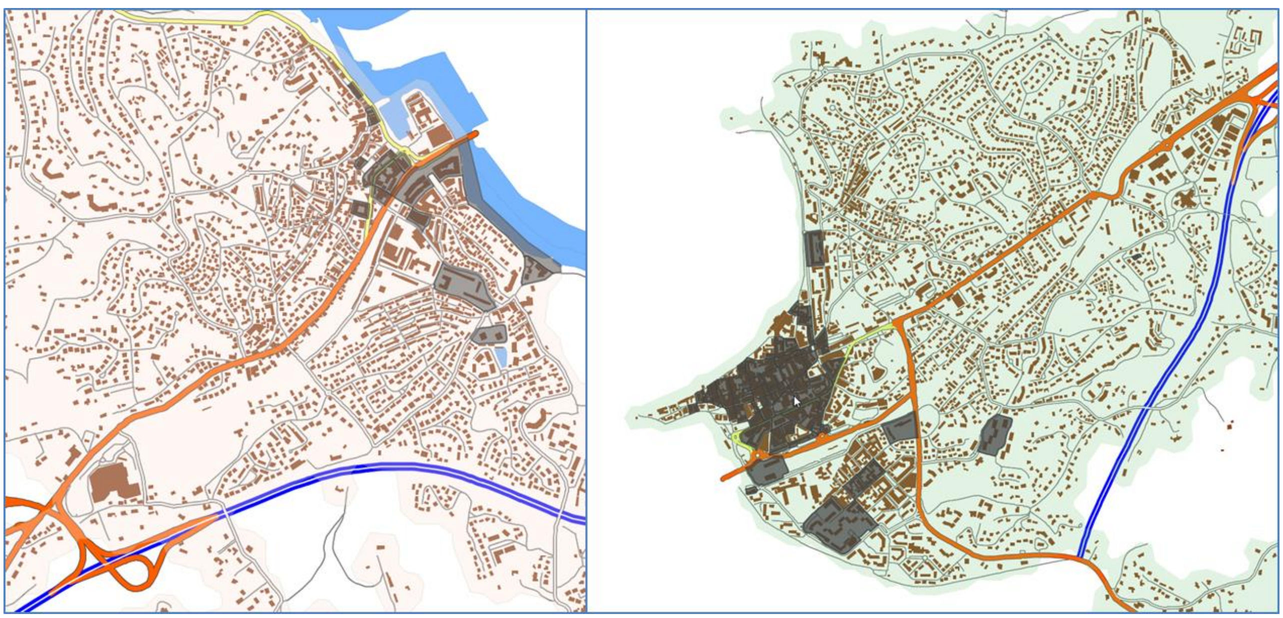

Fig. 3. Inner city block detection with ELECTRE TRI (transparent dark gray blocks), for two towns where the inner blocks are not in the center of the town extent polygon (both are on the seaside).

3.2 Building and Block Classification

The multiple criteria decision technique presented in the previous section does not provide any input to gradually cover the other blocks of the map, once the inner city blocks are covered. That is why we propose to use block classification, and to cover blocks based on this classification. The classes we used in our experiments derive from the building classification proposed by Steiniger et al. (2008): *inner city*, *urban*, *suburban*, *industrial*, *rural*, and *hetero-*

geneous. We first classify buildings using the descriptors from Steiniger et al. (2008) (e.g. size, number of vertices, compactness, density around…) with a Support Vector Machine classifier (Fig. 4). The results are fair, but some strange artefacts remain, with similar and neighbor buildings having different classes, with sometimes jumps in classes. For instance, there is a building alignment in the upper part of Fig. 4 with all buildings classified as rural except two, one being suburban, and one urban. To avoid such artefacts, Steiniger et al. (2008) used a spatial filter to homogenize the outputs of the classification, as similar neighbor buildings should be classified. We did not use this filter, because the homogenization is handled in the next step, and it can explain these artifacts, but there might be several ways to improve the classification, for instance by using the probability given by the learning algorithm.

Then, blocks are classified using the class of the majority of its inner buildings; if there is no class majority in the block, it is classified as *heterogeneous*. This step allows some kind of smoothing of the results of building classification, and replaces the spatial filter used by Steiniger et al. (2008) to homogenize neighbor buildings.

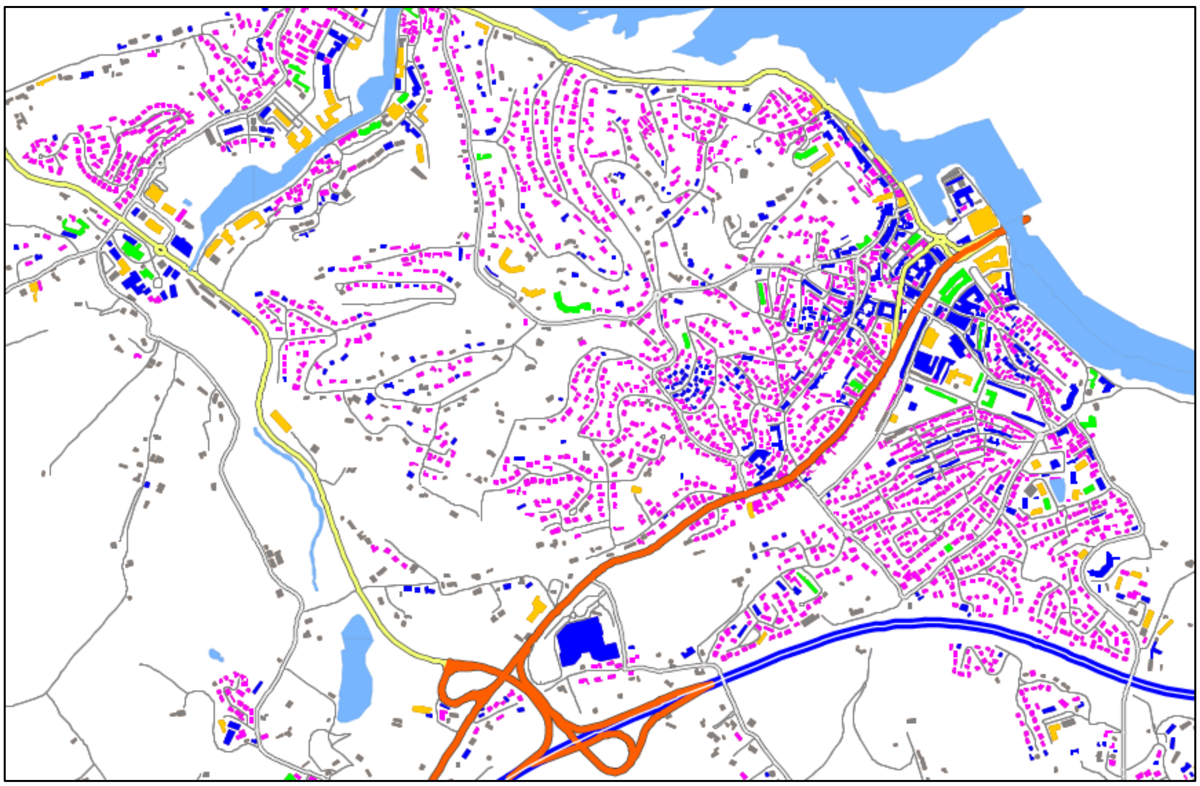

Fig. 4. Building classification result: inner city (green), urban (blue), industrial (yellow), suburban (magenta), rural (gray).

4. Landmarks Automatic Inference

We make the assumption that landmarks can help the map readers to grasp the main spatial relations of the map across scales and to find their way when zooming in or out. "Landmarks are prominent, identifying features in an environment, which provide an observer or user of a space with a means for locating oneself and establishing goals." (Sorrows and Hirtle 1999). In this case, we consider that landmarks are buildings that are prominent due to their symbol (derived from their nature), their size or shape compared to their neighbors, or their position on the map. As our building landmarks are supposed to help the map user navigating across scales, they should somehow be displayed at all scales on top of the covered blocks. If necessary, building landmarks will be enlarged or displaced to be legible at all scales.

Landmarks automatic extraction methods exist in the context of route wayfinding (Elias 2003), and we tried to adapt this method based on machine learning. Table 2 describes the descriptors of the landmarks that are adapted from (Elias 2003), considering the characteristics of a landmark in our use case stated above. As proposed by Elias (2003), a decision tree classification method was used, and the training dataset was the same as the one used in the building classification method presented in the previous section. The results obtained with this method are presented in Fig.5, and match well with what we considered as landmarks, i.e. buildings different from their neighbors and/or that have a specific function (e.g. administrative buildings). The used classification method simply flags the buildings as landmarks or not, with a confidence ratio between zero and one, so the results can be adjusted by changing the confidence ratio threshold (a threshold of 0.97 was used to obtain the results presented in Fig. 5).

Table 2. Descriptors used to qualify buildings as landmarks.

Descriptor name	Description	Why it is used
category	Building semantic category (e.g. public, industrial, unknown…)	Some categories are rendered with a specific symbol making them more salient
compactness	compactness of the building, Miller index (MacEachran 1982)	Buildings with salient shapes are more likely landmarks than regular shaped buildings
elongation	elongation of the building (length/width ratio of the minimum bounding rectangle)	Also characterizes building shape
squareness	total deviation of angles to square angles (Lokhat and Touya 2016)	Also characterizes building shape
density	density of buildings in a 100 m radius	Isolated buildings might be more salient
adjacency	number of adjacent buildings	When attached to another building, a building is less salient
neighbors	number of buildings in a 100 m radius	Isolated buildings might be more salient
crossroad	distance to nearest crossroad	Crossroads are landmarks, so buildings near crossroads might be more salient
size	area of the building	Large buildings might be more salient
orientation	general orientation of the building, i.e. orientation of the longest side of the minimum bounding rectangle (Duchêne et al. 2003)	Buildings with specific orientation compared to the others might be more salient
granularity	number of vertices of the building	Buildings with more granularity might be more salient

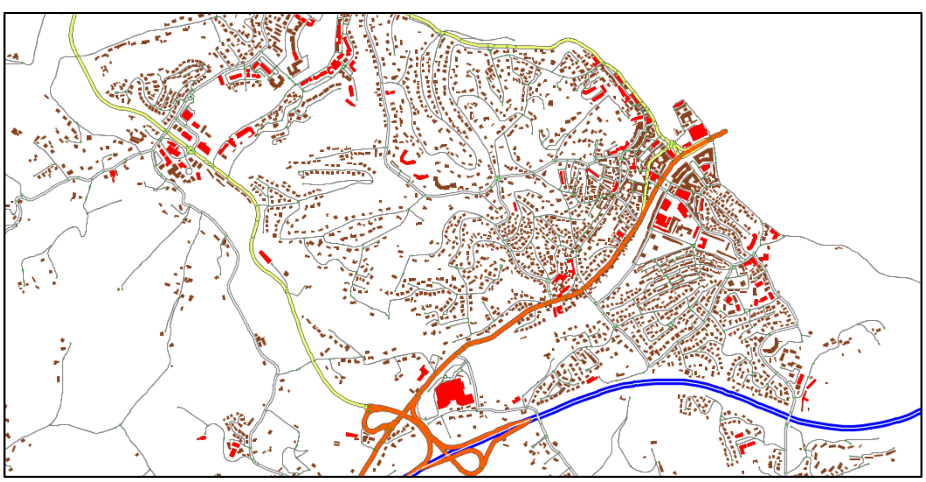

Fig. 5. Result of landmarks automatic inference on 1:25k buildings from IGN (landmarks are displayed in red).

Fig. 6 shows a comparison between the automatic detection and manual selection of the landmarks in the map by a cartographer. Some landmarks chosen by the cartographer are not detected as landmarks by the proposed method, but most of all, there are too many landmarks detected compared to the manual selection that retains only the most salient landmarks.

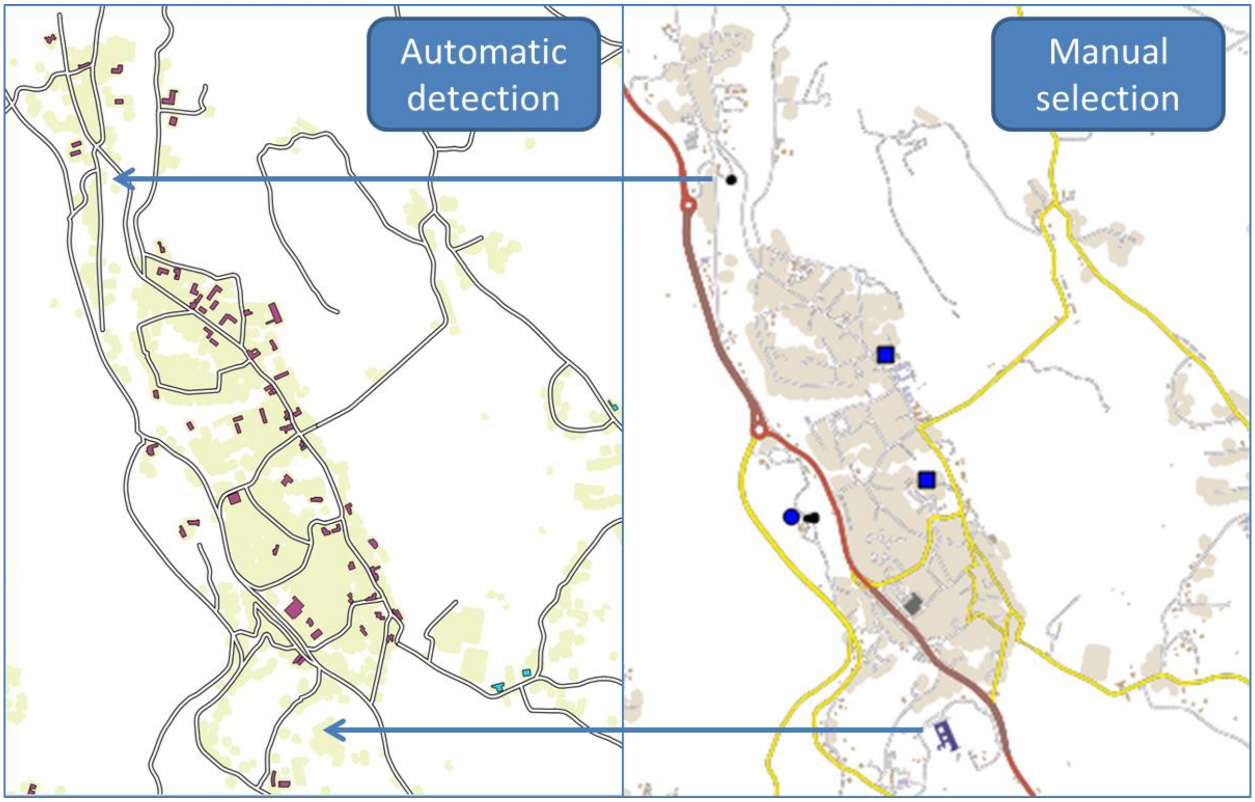

Fig. 6. Comparison between the automatic detection and a manual selection of landmarks: two of the manually selected landmarks are not automatically detected, but most of all, the number of automatically detected landmarks is much bigger.

5. Derivation of Intermediate Scales

In the presented maps, we used the initial 1:25k buildings at all scales, but we plan to use the buildings generalized by the agent-based or typification strategies we are developing in parallel. In this dataset, building semantics is minimal and related to buildings that are rendered differently: public buildings, industrial or commercial buildings, religious buildings, castles, and greenhouses. To be really effective, the intermediate maps should also have their road network generalized (as well as the other map themes), which is not the case here for time issues, so we only present buildings in the figure. The choice of three intermediate scales is quite arbitrary: as we intend to compare the different strategies to build the intermediate scales with a user experiment, it is not possible to test too many options that would make the experiment too long for the user.

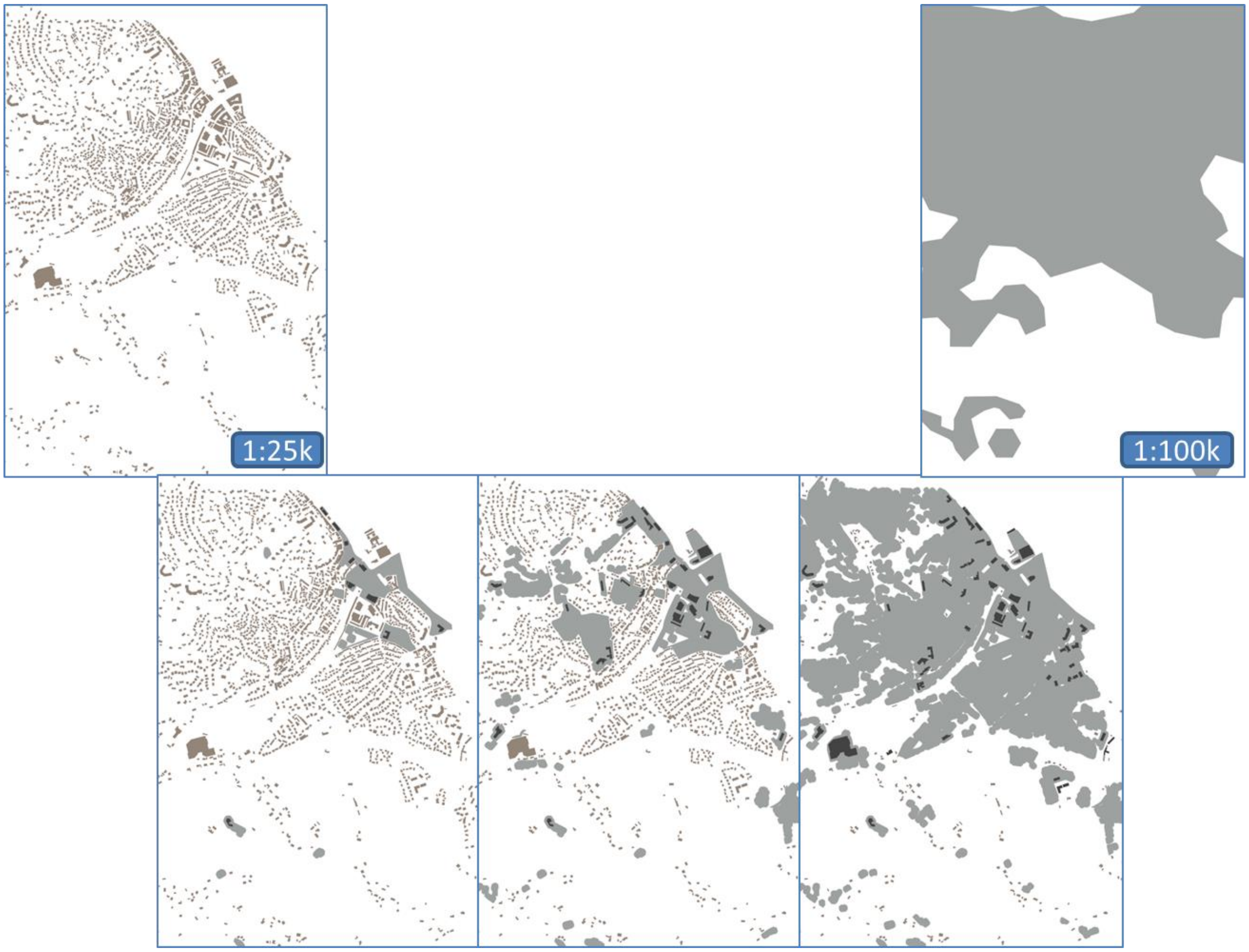

Fig. 6. Gradual transition by block covering with three intermediate scales between 1:25k and 1:100k. The remaining buildings at each scale should be generalized in some way to finalize the building/block/built-up area layers.

6. Conclusions and Discussion

This paper proposes methods to gradually generalize an individual building layer into a built-up area by block covering and highlighting of the building landmarks. Although the methods may largely be improved, the first results are encouraging enough to consider once again machine learning in generalization, because of the recent advances in this domain, as claimed in (Touya 2015).

The proposed methods can all be improved by tuning their parameters, and by spending more time on creating better training datasets. For instance (Weng et al. 2017) proposes a multi-scale landmark extraction method that might better suits our purpose than the method from (Elias 2003) used in this paper. We have seen in Section 3.2 that a building classification was used to infer a block classification: the class of the block is the class of the majority of the buildings in the block (or heterogeneous if there is no class with majority). It might be more effective to directly classify blocks using a similar method. Finally, these gradual intermediate representations or abstractions of the individual buildings will be integrated in a user survey, with alternative methods, to verify that adding intermediate scales does improve the user efficiency while zooming in a geovisualization application, and to learn which generalization strategy is the most effective in this context (Dumont et al. 2017).

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