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Detecting Level of Detail Inconsistencies in VGI Datasets

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Abstract. Whereas it was possible to define the level of detail (LoD) of authoritative datasets, it is not possible for Volunteered Geographic Information (VGI), often characterised by heterogeneous levels of details. This heterogeneity is a curb for map-making, particularly when using traditional map derivation processes such as generalisation. The paper proposes a method to infer the level of detail of VGI features. Then, inconsistencies between features with different levels of detail that get in the way of good mapmaking can be automatically identified. Some proposals are made to harmonise level of detail heterogeneities. The LoD inference is implemented and results are presented on OpenStreetMap data.

Keywords: VGI, OpenStreetMap, level of detail, cartography

1 Introduction

Volunteered Geographic Information (VGI) is more and more used by the GIScience research community but also by all users of geospatial data. Indeed, as crowdsourcing communities, such as the OpenStreetMap community, continuously improve their processes the data quality increases (Girres and Touya 2010, Haklay 2010), encouraging companies and administrations that rely on geospatial data to trust VGI. Even National Mapping Agencies (NMA) that produce authoritative and high quality data intend to integrate VGI in their databases (e.g. Canada). Beyond data quality, validating VGI for use by governments raises issues of integration into authoritative datasets (Du and others 2012) and trust in the volunteers (Skarlatidou, Haklay and Cheng 2011). Moreover, it seems necessary to check if VGI can easily be used in the applications, based on the authoritative data it replaces or enriches. The main application of geospatial data is mapmaking, which can be a very complex task when scale varies and generalisation is required.

VGI and especially OpenStreetMap are successful because of their simplicity (Brando 2012): almost anybody able to use a GPS device is able to contribute, as the specifications are not too complex to handle. The drawback of this simplicity is the heterogeneity of the produced data (Girres and Touya 2010). The level of detail (LoD) of features is particularly heterogeneous. For instance, buildings with street display LoD coexist with land use parcels extracted from satellite imagery. Maps derived from VGI show that inconsistencies in LoD between spatially related features (e.g. a building and a containing built-up area) cause map conflicts (Das, van Elzakker and Kraak

2012), which are big obstacles to good quality mapping. The aim of the paper is to propose a method to identify LoD inconsistencies in VGI datasets. Indeed, if LoD inconsistencies are identified in the map, it is possible to further correct them to make more legible and less confusing maps. The key of our proposal to identify LoD inconsistencies is a two step process: first infer a LoD for each feature of the map and then identify spatial relations between conflicting LoD features.

Section 2 precisely defines the level of detail and its importance in mapmaking. Section 3 presents our proposal to infer the LoD of geographical features and detect inconsistencies. Section 4 shows some results on OpenStreetMap data. Section 5 briefly explores techniques to correct LoD inconsistencies and section 6 concludes and discusses further work.

2 The Importance of Level of Detail

2.1 Scale and Level of Detail

The scale of a map has a simple definition; it is the homothety factor between ground size and map size of features. In cartography, the word scale may also convey representation aspects: features cannot be mapped the same way at each mathematical scale, e.g. buildings can be mapped individually at large scales, e.g. 1:25,000, but are represented as built-up areas at small scales, e.g. 1:200,000.

However, scale cannot be used to characterise geographical databases, because data are not only intended for cartographic representation, and the term level of detail is preferred. Ruas and Bianchin (2002) define the level of detail in a geographical database as the conjunction of the *conceptual schema* of data, the *semantic resolution*, the *geometrical resolution*, the *geometrical precision* and the *granularity*.

The *conceptual schema* component is the way ground truth is represented in the geographical database: representing forests as polygonal features or with point features representing each tree are conceptual schemas that correspond to different levels of detail.

The *semantic resolution* is the quantity of details in the attribute data attached to geographic features. The issue is not related to mapping, so we will not focus on this component in the remaining of the paper.

By analogy with raster resolution, the geometric resolution of vector features is approximately the minimum distance between two vertices of the geometry.

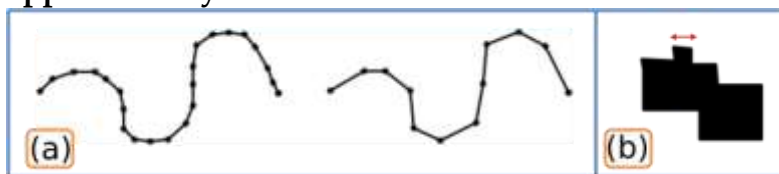


Figure 1a shows that such a definition should be handled carefully as the distance between vertices is always shorter in sharp bends. Like Ruas and Bianchin (2002), we

consider that the resolution value of a database should be used as a rough estimate of the features resolution.

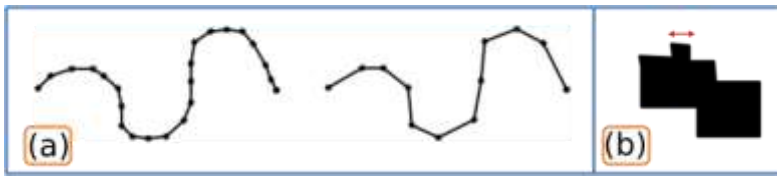


Figure 1. (a) two lines with different resolutions. (b) the granularity of a building.

The *geometrical precision* is simply the positional shift between ground truth and represented feature. *Granularity* describes the size of the smallest shapes of features, e.g. the smallest protrusion of buildings (



Figure 1b).

In the remainder of the paper, we consider LoD as the aggregation of all four components described above. We call high LoD a level of detail with high precision, resolution etc., and low LoD a level of detail with low precision, resolution etc. Despite this definition, LoD is a relative notion that is difficult to measure quantitatively or qualitatively. Section 3.1 of the paper describes of we propose to measure high and low LoD.

2.2 Case studies from OpenStreetMap

In order to illustrate the issue of level of detail inconsistencies and to test our propositions, three case studies were extracted from the French OpenStreetMap (OSM) dataset, as OpenStreetMap is a VGI source aiming at making maps. The case studies cover and share different kind of landscapes: urban, rural, suburban and mountainous areas (Figure 2).



Figure 2. Extracts from the three case studies: an urban area, a mountainous area, and a suburban one ©OpenStreetMap.

All three case studies contain a large amount of LoD inconsistencies, as OSM seeks to indifferently gather very detailed features such as cycle lanes and less detailed features such as sea routes or built-up areas. The inconsistencies are increased by the heterogeneity of capture tools and techniques used by OSM contributors. For instance, capturing a building automatically from cadastral image (as in French OSM), or from GPS field work do not yield similar LoDs.

The most common and obvious type of inconsistency in the case studies is the coexistence of detailed buildings and land use parcels. In Figure 3, buildings intersect a forest limit which is unlikely, or lie just outside the built-up area they should be part of.



Figure 3. Examples of LoD inconsistencies: the upper left buildings intersect the forest limit and buildings on the right lie outside the built-up area ©OpenStreetMap.

Even in rural areas where OSM datasets are less complete, the few existing features are LoD inconsistent. In Figure 4, we can see public bathrooms and an access path connected to less detailed footpaths, which coexist with very undetailed lake and river features. A footpath even crosses the lake because the lake is very imprecise at the footpath level of detail.



Figure 4. Examples of LoD inconsistencies: a public bathrooms spot and its path co-exist with less detailed footpaths (dashed lines) and even less detailed lake and river ©OpenStreetMap.

2.3 Mapmaking with Inconsistent LoDs

Inconsistent LoDs in the source data of a map may cause bad quality maps for two main reasons:

- It causes legibility problems at multiple scales.
- It may convey misleading information.

Inconsistent LoDs may make small scale maps, where high LoD features should not appear, not legible. Indeed, the knowledge of eye perception limits allows the definition of legibility thresholds (e.g. perception, separation, differentiation, etc.): below these thresholds, the eye only perceives noise that disturbs map reading, whatever the map legend is (Duchêne, Christophe and Ruas 2011). Figure 5a shows an extract from OSM standard maps where most buildings are too small to be legible and disturb the reading. Here, generalisation is required, for instance by increasing building size. In the same time, too dense layers cause symbol overlapping problems, such as points of interest on a legible background map (Figure 5b). Although OSM is not designed to make maps with all its features, legibility problems may occur at most scales, even large ones.



Figure 5. (a) The building LoD is inconsistent with roads, rivers and land use LoD bringing noise to the map reader at this scale (©OpenStreetMap) (b) Point of interest symbols overlap at this scale.

Inconsistent LoDs may also convey misleading information to the map reader that is not aware of each feature LoD and interprets the map as consistent. Figure 6 shows an example where inconsistent LoDs between buildings and forest in OpenStreetMap mislead the reader on the fact that buildings are in the forest. The forest LoD should restrict its use to small scale maps where buildings are not represented. Moreover, a map reader traditionally expects consistent LoD and his cognitive interpretation of the map may be biased by the inconsistency.



Figure 6. The forest LoD is inconsistent with the buildings in OSM misleading the reader because buildings are not in the forest but in a clearing.

Finally, automated mapping requires complex processes such as cartographic generalisation to make the geographical information legible at a given scale. Generalisation processes are mostly designed for NMA data that are homogeneous in LoD (Stanislowski and others 2012). Cartographic generalisation of VGI data has not been tackled yet: research projects are starting but do not focus on LoD heterogeneity (e.g. Klammer and Burghardt (2012) focus on generalising tile-based maps) and OSM based projects such as Mapnik¹ or CloudMade² only provide very simple generalisation operations, e.g. line filtering and feature selection. Thus, detecting LoD inconsistencies would greatly help to improve the way maps made with VGI data are perceived by a reader.

3 Detecting LoD Inconsistencies

This section describes our proposed approach to detect LoD inconsistencies: first, the LoD of features is inferred and then, spatial relations between features with different LoD are identified. The first subsection briefly presents the proposed LoD classification that is used to measure LoD. The second subsection deals with the inference of a LoD for individual features, based on criteria derived from LoD components (2.1). The last subsection deals with the detection of inconsistencies that relies on spatial relations.

3.1 Classification of Levels of Detail

LoD is a quite relative and fuzzy concept as its five components cannot be clearly and quantitatively defined, so we propose to measure it qualitatively with a Likert scale (Likert 1935) classification. We defined five LoD categories extracted from French geoportal³ from the most detailed to the least: *street*, *city*, *county*, *region* and *country*.

¹ mapnik.org

² cloudmade.com

³ geoportail.gouv.fr

The *street* LoD contains features represented for parcel management or street orientation, e.g. the British OS MasterMap®. The *city* LoD contains features represented to describe what is visible on the ground (buildings, roads, rivers, forests, etc.). The *county* LoD contains features that represent a small region to allow displacements like the ones of a tourist in the area (i.e. visits, trekking, cycle rides). The *regional* LoD is related to the representation of a large region and the *country* LoD is even less detailed, for the representation of countries or big regions.

The LoD inference described in the next section classifies features in one of these five categories by the means of quantitative and qualitative criteria.

3.2 Assessing Features LoD

3.2.1 Criteria to Assess Geographic Features LoD

The components of LoD presented in 2.1 allow the definition of several criteria that are computed for each feature of the dataset to infer its LoD:

- Feature type criterion (*conceptual schema* component)
- Vertex density criterion (*resolution* component)
- Median edge length criterion (*resolution* component)
- Capture source criterion (*geometrical precision* component)
- Shortest edge criterion (*granularity* component)
- Size criterion (*granularity* component)
- Coalescence criterion (*granularity* component)

Each criterion is designed to give a value normalised between 0 and 1, 1 being the lowest LoD, *country*. The empirical normalisation of each criterion implies some imprecision and fuzziness in the criteria values, which will have to be taken into account by the method using the criteria.

The **feature type criterion** analyses the feature type of features in relation to the data specifications and to a geographical ontology to infer LoD. The presence of some feature types in a map reveals the conceptual schema component of LoD. For instance, buildings or points of interest have higher LoD than built-up areas features.

The **vertex density criterion** analyses the number of vertices compared to feature length to give a clue on geometrical resolution, which is fuzzily defined. To empirically normalise the density, vertex density values have been studied for different types in datasets with different LoDs from the French NMA. The criterion value is computed according to $(\text{vertex_density_value} = (1 - \text{vertexDensity})^8)$ (Eq. 1).

$$\text{vertex_density_value} = (1 - \text{vertexDensity})^8 \quad \text{(Eq. 1)}$$

The **median edge length criterion** analyses the median of edges length between two vertices to complete the assessment of resolution. Girres (2011) states that it is the best criterion to assess geometrical resolution on roads and rivers. A piecewise function from \mathfrak{R} to $[0,1]$ was empirically derived from values in the French NMA datasets and from the conclusion of Girres (2011).

The **capture source criterion** analyses metadata on the capture source of features (e.g. GPS tracks, aerial images) to infer geometrical precision from knowledge on the sources. The values for the OpenStreetMap tag “source” were analysed in several French datasets, and a LoD value was assigned to each source value. For instance, features captured from the national cadastre have a 0.1 value for this criterion while features imported in OSM from CORINE Land Cover dataset (i.e. European land use dataset) have 0.7 value.

The **shortest edge criterion** analyses the length of the shortest edge between two vertices to infer granularity. It is a classical measure to assess building granularity in cartographic generalisation (Stöter and others 2010). It was also calibrated using OSM and French NMA datasets to obtain a piecewise function from \mathfrak{R} to $[0,1]$.

The **size criterion** analyses the size of features to complete granularity inference. Indeed, the presence of small features indicates high granularity. We used the legibility thresholds of eye perception to relate features size to the LoD categories.

Finally, the **coalescence criterion** is dedicated to the inference of linear features granularity. It is based on the principle that if a linear feature symbol coalesces at a given symbol width (Figure 7), it means that the feature cannot be displayed at a scale that requires such a width for eye perception issues (Girres 2011). To relate symbol width to scale and then to LoD categories, we studied the symbols used in the French NMA map series.

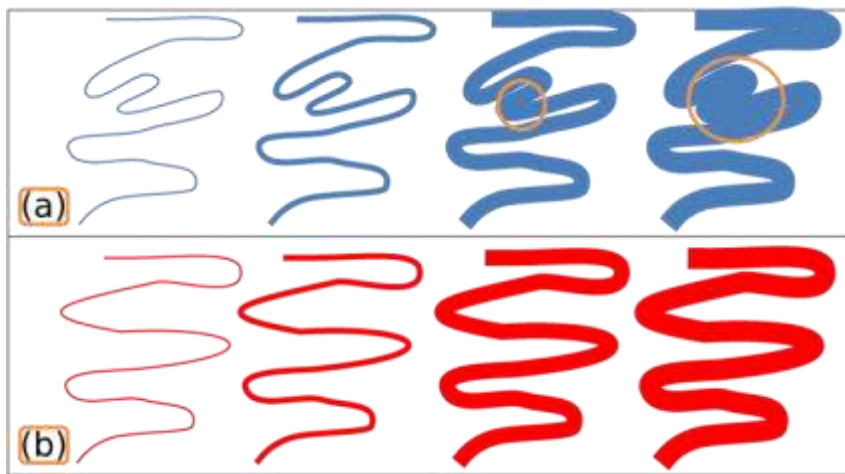


Figure 7. Linear granularity assessed by coalescence tests: (a) line has higher granularity than (b) as it coalesces quicker when symbol width is increasing.

In order to infer a feature LoD from the seven criteria, multiple criteria decision techniques are required. The next section presents the multiple criteria decision method we used, ELECTRE TRI (Figueira, Mousseau and Roy 2005).

3.2.2 Assessing LoD with ELECTRE TRI

Multiple criteria decision analysis is a field of computer science that develops techniques to make an appropriate decision based on multiple criteria. The decision can be: inferring the best element, sorting elements or classifying them. In our case, the

decision we want to make is classify a feature into one of the LoD categories defined above. ELECTRE TRI is a multiple criteria decision method that classifies elements, using the principles of the ELECTRE multiple criteria decision methods (Figueira, Mousseau and Roy 2005). ELECTRE methods only compare elements criterion by criterion and do not compare values from different criteria (i.e. it does not compare apples with oranges). It was previously used in map generalisation by Taillandier and Taillandier (2012).

The ELECTRE TRI method should be used when the following conditions are met (Figueira, Mousseau and Roy 2005):

- Classification into ordered categories (e.g. from ‘street’ LoD to ‘country’ LoD).
- More than 3 criteria (7 here).
- Heterogeneous criteria (e.g. it is hard to compare the granularity and source criteria).
- For some criteria, a small value difference may be not significant, while the addition of several small differences may become significant. It compensates for the imprecision of our criteria.

ELECTRE TRI classifies vectors of values for each criterion (the dimension of the vector is the number of criteria), which correspond to the measured criteria for a given feature. For each category, two vectors are defined representing the lower bound of the category and its upper bound. For instance, for the category ‘street LoD’, the vertex density criterion value ($\text{vertex_density_value} = (1 - \text{vertexDensity})^8$ (Eq. 1) of the lower bound vector is 0 (it is the first category) and the value of the upper bound vector is 0.2.

The ELECTRE TRI principle is to compare the vector for a given feature to the bound vectors of each category using an outranking relation: a feature is classified in a category if its vector outranks the lower bound vector of the category and is outranked by the upper bound vector. The comparison of two vectors, i.e. the computation of the outranking relation, is inferred from the comparison of the vector value for each criterion alone, two different criteria values are never compared (Figure 8). For one criterion, a value can be preferred to the other or both are considered equivalent for this criterion. Using this preference, each criterion votes for the assertion “vector u outranks vector v ” (Figueira, Mousseau and Roy 2005).

$$\begin{array}{c}
 u = \begin{pmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \\ u_6 \\ u_7 \end{pmatrix} \quad v = \begin{pmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \\ v_5 \\ v_6 \\ v_7 \end{pmatrix} \quad \left\{ \begin{array}{l} u_1 > v_1 \\ u_2 > v_2 \\ u_3 = v_3 \\ u_4 > v_4 \Rightarrow u > v \\ u_5 = v_5 \\ u_6 > v_6 \\ u_7 = v_7 \end{array} \right.
 \end{array}$$

Figure 8. In ELECTRE TRI, the comparison between two vectors (i.e. the outranking relation) is inferred from the comparisons for each criterion.

In order to allow this comparison of values for a criterion despite their imprecision and fuzziness, four properties have to be added to criteria:

- *Weight*: it conveys the importance of this criterion compared to the others.
- *Preference* threshold: if the difference between values for this criterion is bigger than preference, the vector with bigger value is preferred considering this criterion. It adjusts to the normalisation used for the criterion. For instance, vertex density has a 0.2 preference while size has a 0.5 preference.
- *Indifference* threshold: if the difference between values for this criterion is less than indifference, both vectors are considered as equivalent for this criterion. For instance, for shortest edge, a difference less than 0.25 is not significant.
- *Veto* threshold: if the difference between values for this criterion is bigger than veto, than the vector with bigger value will always be preferred to the other, whatever the other criteria. For instance, size has a high veto threshold as it is never possible to infer LoD only with this criterion.

The output of the ELECTRE TRI method for a given feature is its LoD category with a confidence rate on the classification, e.g. “this particular road feature has a topographic LoD with 80% confidence rate”.

3.3 Spatial Relations Based LoD Inconsistencies Detection

Taking into account spatial relations is fundamental in automatic mapmaking and generalisation (Duchêne, Ruas and Cambier 2012). Brando, Bucher and Abadie (2011) state that the identification of implicit spatial relations helps to define good specifications for VGI contributors. (Brando 2012) follows the idea proposing to add integrity constraints checking on spatial relations in VGI contributing software (e.g. verify that roads do not cross buildings or that bus stops are along roads). We believe that the same approach could be used to identify places where LoD heterogeneity is a problem for mapmaking. If two features should respect a spatial relation for integrity reasons but do not, and if the features involved in the relation have a different LoD, there is a LoD inconsistency (Figure 9a). Conversely, if a forbidden spatial relation does exist with involved features having a different LoD, there is a LoD inconsistency (Figure 9d).



Figure 9. (a) building should be inside built-up area. (b) no intersection between paths and lakes. (c) bus stop should be along the road. (d) a group of houses should be in a clearing ©OpenStreetMap.

Therefore, the proposed method uses as parameters a set integrity spatial relations and automatically process features to identify instances of these relations between LoD different features. For instance, if the set of integrity relations contains the four spatial relations depicted in Figure 9, the method searches the instances of buildings just outside a built-up area, etc. The reification of relations follows Duchêne, Ruas and Cambier (2012) idea that defines spatial relations instances to guide generalisation.

4 Application on OpenStreetMap Case Studies

The criteria for individual LoD inference have been calibrated with features from zone 3 (see 2.2) and tested on both remaining zones. The method was implemented on CartAGen open source generalisation platform (Renard, Gaffuri and Duchêne 2010). Figure 10 shows some of the automatic inferences on road, building, path or land use features. As expected land use parcels are classified as LoD 1 (*street* LoD) as they are imported from European dataset CORINE Land Cover. Buildings, imported from cadastral maps, are mostly classified as LoD 5, but large buildings, that have fewer details, have a lower LoD. Roads are classified heterogeneously: some very

detailed features such as the cycle lanes at the bottom right of Figure 10 are classified as LoD 4, while straight important roads are classified as LoD 2. After evaluation of the zone, results comply with a visual assessment of LoD.



Figure 10. Some results of individual LoD inference in zone 2.

Figure 11 shows how buildings found in zone 2 can be classified into different LoDs, depending on their characteristics (only granularity, resolution and precision may vary here).



Figure 11. Illustration of the individual LoD inference of some highlighted buildings in zone 2.

Then, the four spatial relations from Figure 9 are selected as a set of relations to identify LoD inconsistencies: (i) building should be inside built-up area; (ii) no intersection between paths and lakes; (iii) bus stop should be along the road; (iv) a group of houses should be in a clearing. Instances of these relations between LoD inconsistent features were automatically computed in the case studies. Figure 12a shows a group of houses inside a forest whose LoD explains the lack of clearing around the group. Figure 12b shows buildings identified as lying just outside a low detail built-up area. Figure 12c shows with the red cross a bus stop too far to be along the road unlike the two at the bottom of the picture. Figure 12d shows a detailed footpath intersecting a low detail lake.

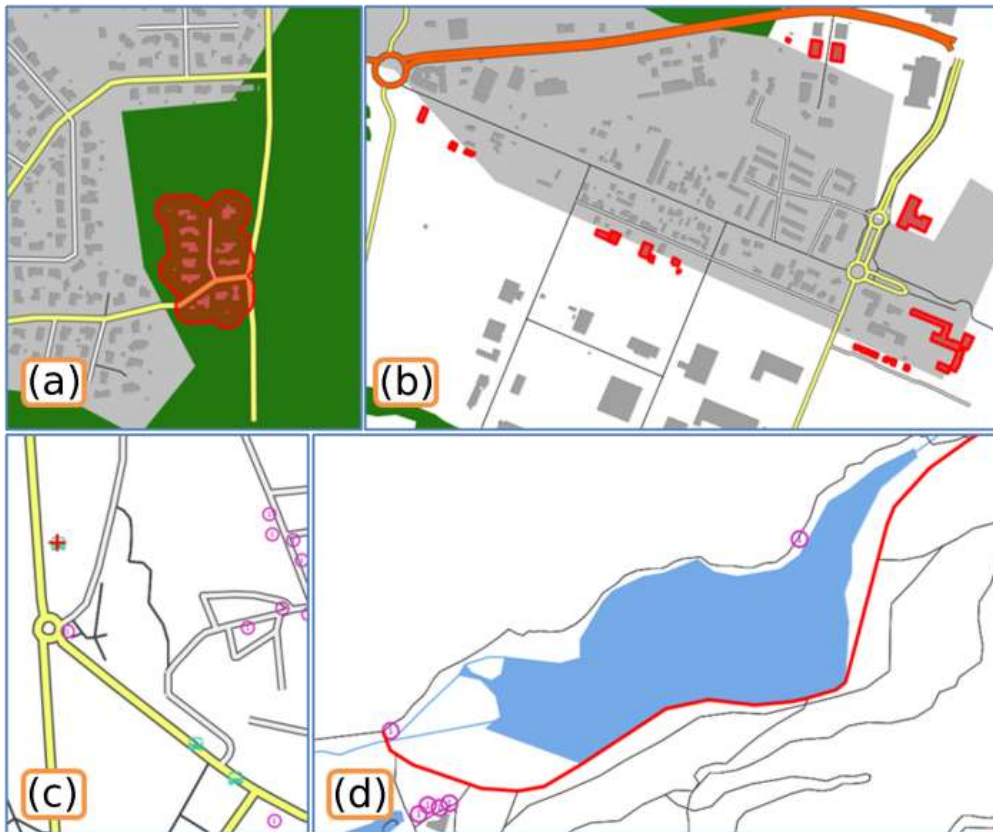


Figure 12. Automatic detection of LoD inconsistencies for the four selected spatial relations (highlighted in red).

5 Resolving LoD Inconsistencies

Since LoD inconsistencies prevent good quality maps, strategies have to be developed to resolve the inconsistencies. When the aim is to make a map at a given scale from VGI, three strategies can be used. This section discusses the strategies but we have not implemented them yet.

The first strategy would be to build a multiple-resolutions database (MRDB) out of the VGI dataset as proposed in (Müller and Wiemann 2012). It would allow adapting the displayed content to the representations corresponding to a given LoD. Building a MRDB would require matching techniques, maybe benefiting from linked data (Hahmann and Burghardt 2010).

The second strategy would be the harmonisation of LoDs to the closest LoD to the map scale. When trying to make a map at a small scale, the harmonisation is the generalisation of the high LoD features, with specific constraints to correct the LoD inconsistencies. When trying to make a map at a large scale, the harmonisation is the enhancement of the low LoD features that have LoD inconsistencies. Figure 13 shows a simple automatic tool we developed on CartAGen open source generalisation platform (Renard, Gaffuri and Duchêne 2010), which enhances the built-up area LoD to put the buildings that should be in the area back into it: buffers are computed around the buildings belonging to the identified inconsistent relations and then merged with

the built-up area. This tool is suited for harmonising undetailed areas that contain very detailed features and similar tools should be developed for the other types of LoD inconsistencies.



Figure 13. Initial data (©OpenStreetMap) with several buildings outside a low LoD built-up area. The correction (automatically obtained) increases the built-up area LoD and includes the inconsistent buildings in it.

The last strategy is to act when the VGI dataset is compiled, or updated, by automatically proposing a reconciliation if the contribution introduces LoD inconsistency. Brando (2012) proposed a reconciliation tool to avoid integrity constraints violation during VGI contribution: for instance, it displaces the building off a road if a contribution introduces a building on a road. Harmonisation tools could reconcile contributions the same way for LoD inconsistencies, e.g. extend the built-up when a building is added near its limit.

6 Conclusion and Future Work

To conclude, the paper presented the problems raised by the LoD heterogeneity of VGI for mapmaking and proposed a method to infer the LoD of VGI features as a starting point for solving the problem. The method was successfully applied to French OpenStreetMap data.

As pointed all along the paper, there is still a lot to do to handle LoD heterogeneity problems in automatic mapmaking procedures. First, it would be interesting to integrate semantic resolution in LoD, using the ideas of Mooney and Corcoran (2012) on heavily edited OSM objects. Then, it is necessary to adjust LoD inferences considering populations and not only individual features. Clutter (i.e. visual overload, Rosenholtz, Li and Nakano 2007, Stigmar and Harrie 2011) or high local density of features should increase the LoD of the concerned features. Moreover, the techniques presented for correcting LoD inconsistencies are just basic ideas that require further research. Finally, it would be interesting to study the sensitivity of existing automatic generalisation procedures to data with LoD inconsistencies. It would help to identify the weaknesses of these procedures regarding LoD homogeneity and correct them like Stanislawski and others (2012) did for river network pruning.

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