

An evaluation of measures for quantifying complexity of a map

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Abstract

A real-time map must not be too complex. Therefore, we need measures of map complexity that could guideline the real-time generalisation process. In this paper we evaluate measures of *information amount* and *spatial distribution of information*. The evaluation is performed by (1) defining measures, (2) implementing the measures, (3) computing the measures for some test maps, and finally (4) comparing the values of the measures with human judgement of the map complexity. For information amount, we found that the measures *object line length* and *number of objects* had better correspondence with human evaluation than *number of points* and *object area*. However, this result is based on testing only one object type – building objects – which make the it not possible to draw any general conclusions. We also found that measures based on the size of Voronoi regions (of objects respective points) can be used for identifying spatial distribution of information.

Keywords: information amount, complexity, cartography, generalisation, constraints

1. Introduction

A major issue in cartography is the usability of the map. For traditional paper maps this has been studied thoroughly, but the new technology of the last decade has made new types of map usage possible. A growing type of usage is interactive real-time applications e.g. for the web and mobile devices. These maps can be tailored for a specific purpose and even for a specific user (Reichenbacher 2004, Gartner 2004). This large freedom to tailor sets requirements on new analytical measures, or constraints that describe the usability of the map.

In recent years, the generalisation research has tried to model the overall process of generalisation using constraints (Harrie and Weibel 2007). A constraint can be seen as requirements that should be obtained in the generalisation process. The constraints can be classified into the following types (cf. Ruas and Plazanet 1996, Weibel and Dutton 1998, Harrie 2003): *position, topology, shape, structural, functional* and *legibility*. The five first types concern the representation, i.e. vital aspects of the map should not be lost in the generalisation process. The final type, legibility constraints, concerns the readability of the map.

There are two major types of legibility constraints of a map. The first type concerns the visual perception. The map objects must be readable for a normal user. Robinson (1952, in MacEachren 1995) suggested that cartographic objects should be designed considering human perception, using e.g. a definition of the smallest noticeable lettering size difference. For screen maps the paper map definitions can be rather coarse (Spiess 1995), why specific definitions are needed.

The other type of legibility constraints concerns map complexity. Even though the map objects, and features within the objects, are large enough the map reader cannot comprehend the map if it is too complex (cf. Björke 1996, Li and Huang 2002). The complexity has an even greater importance in real-time maps than for traditional paper maps, as real-time maps should be read and understood relatively fast. Therefore we should strive for establishing measures for how complex a real-time map is allowed to be and let these measures act as constraints in the real-time generalisation.

The aim of this study is to evaluate some measures of map complexity that eventually should be used as constraints in real-time generalisation. The paper is organised as follows. Section 2 includes a literature review of map complexity. In section 3, we divide map complexity into the properties: *amount of information*, and *information distribution*; then, we propose some analytical measures for each of these properties. These measures are evaluated in a case study. The paper ends with conclusions.

2. Background

In order to present a suitable amount of information in a map we need some sort of measure or guidelines. This turns out to be a delicate problem. First we need to specify the word information; what is information, and how can it be measured? According to Kellog (1995), “information technically refers to a reduction in uncertainty about events”. Information thus gives us a specification of the so called events, what is important and what is not. How do we then measure this importance? Can we somehow quantify it?

Bjørke (1996) discusses this matter and the use of Shannon information theory (or “The Mathematical Theory of Communication”, Shannon and Weaver 1964) in cartography. Previously this approach has received some criticism as it does not cover all aspects of information in a map. The critics have argued that, as the theory decomposes the reality into simple elements, it misses the information in the map that is derived from the reader’s previous knowledge. However, Bjørke points out that there are three aspects of information: syntactic, semantic, and pragmatic. While the syntactic aspect deals with the relationship among the symbols, the semantic deals with the meaning of the symbols, and the pragmatic with their application.

The semantic and pragmatic aspects of information are very subjective. They are to a great extent depending on the individual map reader; his/her preferences, opinions, and previous knowledge; but also on cultural and social factors, and the purpose of the map. Quantifying these aspects of the information is very complex, if not impossible. However, if separating the syntactic part of the information from the semantic and pragmatic, we can isolate the factual parts of the information, the objects themselves. Here we have a better opportunity to make a quantification, and use the information theory, as also argued by Bjørke.

One idea to quantify the map information is simply to count the number of objects in the map. However, looking at individual objects might not give a proper quantification as the map reader’s subjective assessment has a major impact. How does the individual map reader determine what is one object? One segment of the road? One road line, from start to end points? One road network? Also, what impact does the visual distance have? Perhaps objects with different attribute types are regarded as different, while objects of the same attribute type are not. Another idea is to express the amount of information as number of object points in the map. According to Biederman (1985) e.g., the human brain attaches great importance to the use of object points when reading and interpreting images, why these points would provide a suitable basis for the calculation of amount of information. Yet some other ideas are to calculate the map area proportion covered by map objects, or the total line length of the objects (lines and polygons only).

Previous work in this area is often based on the Shannon Information Theory (Shannon and Weaver 1964). This theory is intended for message communication, and calculates the information content (entropy, H) in a sent message:

$$H = - [p_1 \log_2 p_1 + p_2 \log_2 p_2 + \dots + p_n \log_2 p_n] \quad (1)$$

where p_i is the probabilities for the messages or symbols i .

Sukhov (1967, 1970; in Li and Huang 2002) applied this theory on cartographic communication in order to measure the information content in maps. The entropy (H_{IC}) was then calculated from the proportion of each object type in the map:

$$p_i = \frac{K_i}{N} \quad (2)$$

where p_i is the probabilities for the object types $i = 1, 2, \dots, n$,

K_i is the number of symbols for object type i , and

N is the total number of map symbols.

$$H_{IC} = - \sum_{i=1}^n p_i \log(p_i) \quad (3)$$

However, as pointed out by Li and Huang (2002), this measure does not consider the spatial distribution of the objects. The entropy will be the same whether the object are tightly assembled or more widespread, the same that applies for the four measures described in the previous paragraph (number of objects, number of object points, object area, and line length). Li and Huang argue that the spatial distribution influences the map

complexity, why the entropy calculation also should involve this aspect. Instead of using so called information amount measures, spatially influenced measures are recommended. To identify the “region of influence”, thus the empty space surrounding each map object, Voronoi regions are used. Three measures are introduced: geometric, “topologic”, and thematic. The geometric measure calculates the entropy of the Voronoi regions. The probability (p) for each object is calculated as the ratio between its Voronoi region size and the total map size:

$$p_i = \frac{S_i}{S} \quad (4)$$

where p_i is the probabilities for the map objects $i = 1, 2, \dots, n$,
 S_i is the Voronoi area of the map objects $i = 1, 2, \dots, n$, and
 S is the total map area.

The total map entropy for spatial distribution (H_{SD}) is then calculated as:

$$H_{SD} = \sum_{i=1}^n p_i \log p_i \quad (5)$$

Thus, when the map contains regions of equal size, the entropy is larger with fewer regions. Also, maps containing an equal amount of regions have a larger entropy the more equally sized the regions are.

The “topologic” measure considers the Voronoi neighbours. Based on the ideas of Neumann (1994, in Li and Huang 2002), the average number of neighbours (ANN) for each Voronoi region:

$$ANN = \frac{N_S}{N_T} \quad (6)$$

where N_S is the sum of the neighbours for all map objects’ regions, and
 N_T is the total number of map objects.

The thematic measure calculates the entropy of the neighbour types. Based on the assumption that the complexity increases when the objects are mixed, thus having neighbours of different types than themselves, the types of each object region’s neighbours are considered. For each object region the probability (p) is calculated as the ratio between the number of neighbours of the same type as the object in question and the total number of neighbours:

$$p_j = \frac{n_j}{N_i} \quad j = 1, 2, \dots, M_i \quad (7)$$

where n_j is the number of neighbours of the same object type j , and
 N_i is the total number of neighbours.

The entropy of the object type i is calculated as:

$$H_i = \sum_{j=1}^{M_i} p_j \log(p_j) \quad (8)$$

and the total map entropy (H_T) is calculated as:

$$H_T = \sum_{i=1}^N H_i \quad (9)$$

3. Our study

The study described in this paper aims at evaluating some measures of map complexity. A previous study (Stigmar 2006) was based on the measure of number of object points in the maps (i.e., amount of map information). However, as Li and Huang (2002) point out, this measure might not capture the complexity of the map information that is based on the spatial distribution. Therefore in this study we also include measures of spatial distribution of map information. The study was conducted as follows:

- 1) Defining a number of measures of map complexity (Subsection 3.1).
- 2) Implementing the measures (Subsection 3.2).
- 3) Selecting a number of maps and evaluating the complexity of these maps (Subsection 3.3).
- 4) Computing the values for the complexity measures for all maps (Subsection 3.4).
- 5) Comparing our evaluation of map complexity with the computed measures (Subsection 3.5).

3.1 Measures of map complexity

The used measures should be both measures of the information amount and measures of the information distribution. We chose to use the four measures of information amount: *number of objects*, *number of object points*, *object line length*, and *object area*. For information distribution we studied both the distribution of points and objects.

Number of objects

The simplest measure counts the number of objects in the map (*NO*). The amount of information is calculated as the total sum of all map objects.

$$NO = \sum_{i=1}^n \sum_{j=1}^{m_i} o_{ij} \quad (10)$$

where o_{ij} is the map objects,

n is the number of object types,

and m_i is the number of objects for object type i .

Number of points in the objects

Based on the ideas of Biederman (1985), the object points can be thought to reflect the amount of work we need to perform in order to perceive an image. Thus, this relatively simple measure counts the total number of object points for all map objects (*NP*) (cf. Stigmar 2006).

$$NP = \sum_{i=1}^n \sum_{j=1}^{m_i} \sum_{k=1}^{p_{ij}} b_{ijk} \quad (11)$$

where b_{ijk} is the points,

and p_{ij} is the number of points for object o_{ij} of object type i .

Object line length

This measure counts the total line length for the map objects (*OLL*; unfortunately not applicable for point objects). The amount of information is calculated as the total sum of the line length of all line and polygon map objects.

$$OLL = \sum_{i=1}^n \sum_{j=1}^{m_i} l_{ij} \quad (12)$$

where l_{ij} is the line length of object o_{ij} of object type i .

Object area

This measure counts the total area of the map objects (*OA*; unfortunately not applicable for point objects). The amount of information is calculated as the total sum of the object areas of all line and polygon map objects.

$$OA = \sum_{i=1}^n \sum_{j=1}^{m_i} a_{ij} \quad (13)$$

where a_{ij} is the area of object o_{ij} of object type i .

Spatial distribution of objects

This measure is based on Li and Huang's (2002) geometric measure, which calculates the entropy of the map objects' Voronoi regions (Equation 4-5). The problem with this measure is that it cannot cope with maps that have different number of objects. To circumvent this problem, as also suggested by Li and Huang's (2002), we normalise the entropy value with the maximal entropy value for the same number of objects (i.e., the case when all Voronoi region are of equal size). Hence, we obtain the following index (HI_{SD_Obj}):

$$HI_{SD_Obj} = \frac{\sum_{i=1}^n p_i \log p_i}{\sum_{i=1}^n \frac{1}{n} \log \frac{1}{n}} = \frac{\sum_{i=1}^n p_i \log p_i}{\log \frac{1}{n}} \quad (14)$$

where p_i is given by equation 4 and n is the number of objects.

The index will be equal to 1 if all Voronoi regions are of the same size and will be smaller the more uneven the Voronoi regions sizes are.

Spatial distribution of points

In our analysis of the spatial distribution we also compute an index for point distribution (HI_{SD_Poi}), with an analogous definition:

$$HI_{SD_Poi} = \frac{\sum_{i=1}^k p_i \log p_i}{\log \frac{1}{k}} \quad (15)$$

where p_i is the relative size of the Voronoi region for point i and k is the number of points.

3.2 Implementation

The measures were implemented using open source Java packages *JTS Topology Suite* (JTS) and *JTS Unified Mapping Platform* (JUMP) (JUMP project 2007). JTS conforms to the *Simple Features Specification for SQL* (developed by Open Geospatial Consortium) and contains a robust implementation of the most fundamental spatial algorithms (in 2D). JUMP contains import and export functions for geographic data (GML, shape, etc.) as well as a viewer. In order to create Voronoi regions we used the c-program Triangle (Shewchuk 1996, 2002) integrated using Java native interface (Gordon 1998).

Figure 1(left) shows the Voronoi region for each point for a test map. To compute the Voronoi regions for objects we merged the Voronoi regions for the points in each objects. This is an approximation; to improve this approximation we introduced fictitious points on long line segments (these fictitious points are not included when computing the object points, equation 11). Still, as seen in Figure (right), the Voronoi regions for the objects are not perfect. There are problems for close lying building objects and especially for building objects that touch each other (which occur a few times in our test data). For the latter our methodology gives overlapping Voronoi edges, which of course is not appropriate. However, these shortcomings will not substantially affect the complexity measures based on the Voronoi regions in our study (Equations 14 and 15).

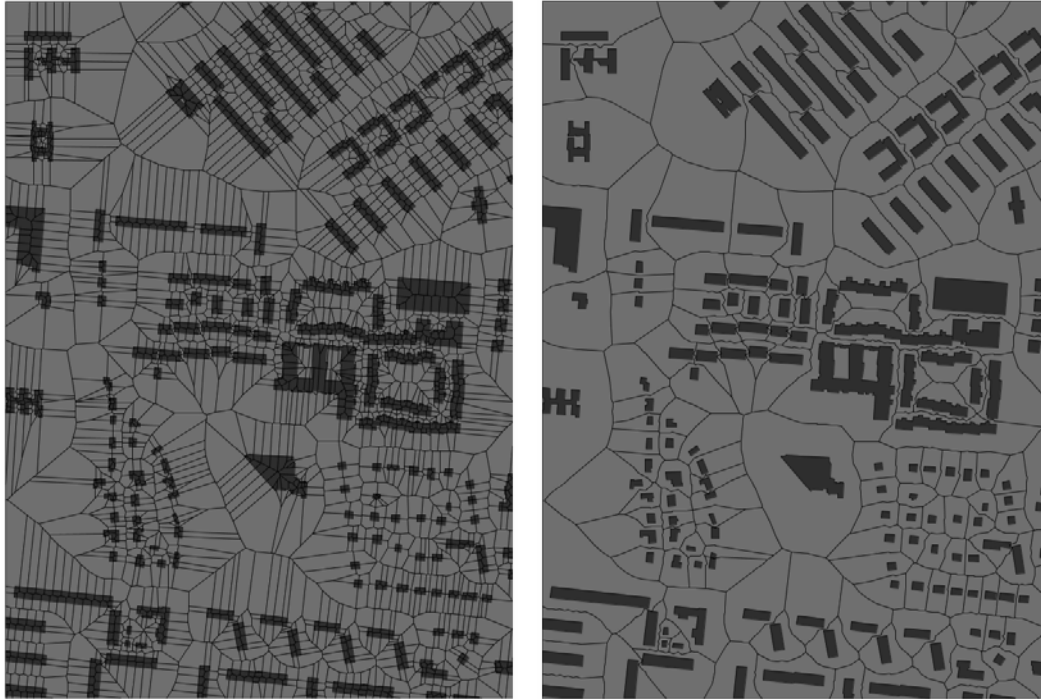


Figure 1: (left) Voronoi regions for each point in the map. Fictitious points are introduced on long line segments. (right) Voronoi regions for each object.

3.3 Test maps and evaluation of their complexity

The test used small-size (paper) maps, appropriate for some commonly used cell phones, with differing amounts of information, or complexity. The used maps were taken from the map Skånekartan (Geodatacenter Skåne, 2007). The first step was to identify suitable map cover locations. The original map data was intended for topographic maps of scale 1:10 000, but in order to get test maps of even greater complexity we used them in scale 1:15 000. Seven locations were found. For the complexity evaluation only building objects were used; but for visualisation purposes we also included roads and in some cases water bodies (as line objects) in the map. The buildings were then generalised using an algorithm developed and implemented by Hampe and Sester (2004) to five generalisation levels. The algorithm simplifies polygons by removing all features of a polygon that were shorter than a parameter value. When the maps were generalised two or three generalisation levels were selected for each area. The selection was based on the maps to be as evenly distributed as possible in the “complexity span”; we avoided to use generalization levels that were rather similar. The maps are shown in Appendix 1.

The complexity evaluation of the maps was performed individually by two evaluators (the authors). The evaluators listed individually the test maps in order information amount. It turned out that the two evaluators had similar opinions about the information amount in the maps, only a few maps were ranked differently. Given below is a common list of the ranking (starting with the map with most information, cf. Appendix 1):

- | | |
|---|------------------------|
| 1. location IV, generalization level (GL) 1 | 11. location I, GL 1 |
| 2. location IV, GL 2 | 12. location VI, GL 3 |
| 3. location V, GL 1 | 13. location I, GL 3 |
| 4. location IV, GL 3 | 14. location II, GL 1 |
| 5. location V, GL 2 | 15. location II, GL 3 |
| 6. location III, GL 1 | 16. location VII, GL 1 |
| 7. location V, GL 3 | 17. location VII, GL 3 |
| 8. location III, GL 2 | 18. location II, GL 5 |
| 9. location III, GL 3 | 19. location VI, GL |
| 10. location VI, GL 1 | |

The test maps were divided into four groups depending on the spatial distribution information (Table 1).

Table 1: Human interpretation of the spatial distribution of building objects in the test maps.

Even distribution of buildings in the map. (Group 1)	Few large building in one area and small buildings in other areas in the map. (Group 2)	Buildings only present at certain areas in the map. (Group 3)	The distribution varies in the map (but buildings are of relatively similar size). (Group 4)
location III, GL 1	location I, GL 1	location II, GL 5	location V, GL 1
location III, GL 2	location I, GL 3	location VI, GL 5	location V, GL 2
location III, GL 3	location II, GL 1		location V, GL 3
location IV, GL 1	location II, GL 3		
location IV, GL 2			
location IV, GL 3			
location VI, GL 1			
location VI, GL 3			
location VII, GL 1			
location VII, GL 3			

3.4 Computing values for the complexity measures

The values for the complexity measures (Equations 10-15) were computed for all test maps (Table 2) using the Java/c program described in Section 3.2.

Table 2: Values for the complexity measures for all test maps.

	<i>NO</i>	<i>NP</i>	<i>OLL (m)</i>	<i>OA (m²)</i>	<i>HI_{SD-Obj}</i>	<i>HI_{SD-POI}</i>
I1	162	1083	12593	70816	0.9115	0.9117
I3	126	542	10476	68416	0.9294	0.9245
II1	86	1073	9855	39269	0.8819	0.8314
II3	86	475	8006	36269	0.8669	0.8459
II5	10	81	2445	16232	0.7970	0.8191
III1	178	1409	16609	73134	0.9314	0.9320
III2	179	877	16117	73456	0.9335	0.9415
III3	151	664	14576	70415	0.9426	0.9384
IV1	427	4092	43556	180621	0.9314	0.9602
IV2	410	2530	41249	179684	0.9335	0.9686
IV3	322	1647	32998	161877	0.9426	0.9723
V1	397	3321	33563	129438	0.9235	0.9298
V2	377	2090	31527	127949	0.9257	0.9373
V3	281	1353	24250	112205	0.9393	0.9432
VI1	287	1521	16773	52384	0.9288	0.9325
VI3	220	924	12789	44078	0.9140	0.9143
VI5	12	88	1506	7371	0.8099	0.6812
VII1	77	582	11461	94643	0.9367	0.9314
VII3	71	363	10848	94476	0.9388	0.9317

3.5 Discussion

Ideally, we would like measures of map complexity that correspond to our human judgement of complexity. In this study we have looked at two categories of complexity: *information amount* and *information distribution*. Figure 2 provides data about the correspondence between the analytical measures of information amount and the judgement done by the evaluators. It seems as the best correspondence is found by *object line length (OLL)* and *number of objects (NO)*. It might be somewhat surprising that the *number of objects* provides a better correspondence with the human evaluation than the *number of points (NP)*. However, it should be noted here that we only used one type of objects (buildings) in this study and also that the objects are similar in structure. The measure *object area (OA)* provides, as expected, bad values in those cases where the building objects are comparatively small/large (see especially map VII,1 and VII,3 which contain mainly large buildings).

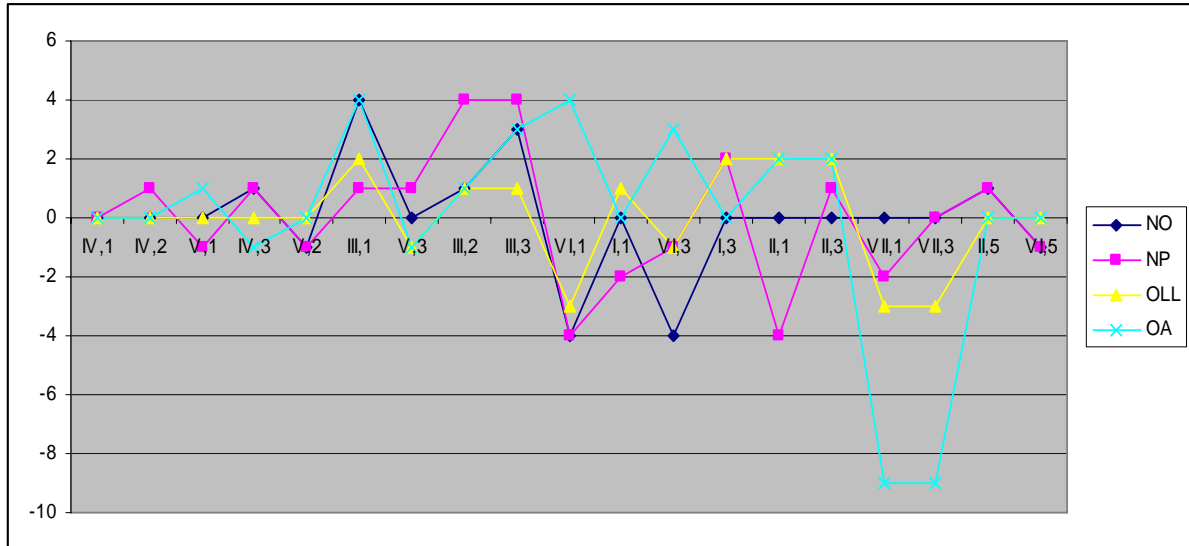


Figure 2: Correspondence between information amount judged by human evaluators and analytical measures (*NO*-number of objects; *NP* – number of object points; *OLL* – object line lengths; *OA* – object area). On the horizontal axis the test maps are given (ordered with decreasing information amount). On the vertical axis is a comparison between the information amount judged by the evaluators and given by the measures. E.g. test map location III, generalisation level 1 (III,1) are judged by the evaluators to be the test map with the 6th most information. The same test map came in 7th position in respect to the number of points (NP). Then, NP is set to 1 (=7-6) for test map III,1. That is, an analytical measure that is close to zero for all test maps corresponds well to the judgement of the evaluators in terms of information amount.

In Table 1 we defined four groups depending on the spatial distribution of information (building objects). We computed the mean and standard deviation of the spatial distribution measures for these four groups (Table 3). The statistical material is fairly small to make any definite conclusions, but it seems likely that:

- both measures can be used for identifying test maps where building objects are only present at certain areas (group 3) and possibly also for where the building size varies in the map (group 2).
- the measures are inadequate to identify minor changes in spatial distribution of objects (comparing group 1 and group 4).

Since we are only using one object type for this study with similar structure (building objects) the two measures based on points and objects (Equations 14 and 15) give similar values. This is likely to be changed if other object types are introduced where the relationships between points and objects are different.

Table 3: Normalised entropy values for spatial distribution of objects (H_{SD-OBj}) and spatial distribution of points (H_{SD-POj}). The values are described for the groups defined in Table 1 using the mean value and standard deviation.

	Even distribution of buildings in the map. (Group 1)	Few large building in one area and small buildings in other areas in the map. (Group 2)	Buildings only present at certain areas in the map. (Group 3)	The distribution varies in the map (but buildings are of relatively similar size). (Group 4)
Mean H_{SD-OBj}	0,93333	0,897425	0,80345	0,9295
Standard deviation H_{SD-OBj}	0,008265	0,028245	0,009122	0,008558
Mean H_{SD-POj}	0,94229	0,878375	0,75015	0,936767
Standard deviation H_{SD-POj}	0,018694	0,046545	0,09751	0,006716

Even if the measures (Equations 14 and 15) succeed in identifying spatial distribution of information, they are incapable of identifying the regions in the map where the information is dense. That is, the measures are

incapable of identifying areas that should be generalised since it is too complex. A better approach might be to divide the original map in regions and compute the information amount for the regions separately. On the other hand, the measures of spatial distribution can be used for identifying that information is spread evenly in the map. And this will probably be an interesting property in future small-display cartography.

4. Conclusions

The aim of this study is to evaluate some measures of map complexity that eventually should be used as constraints in real-time generalisation. We defined and implemented some measures for information amount and spatial distribution of information. For information amount, we found that the measures *object line length* and *number of objects* had better correspondence with human evaluation than *number of points* and *object area*. However, this result is based on testing only one object type – building objects. It is not possible to make any conclusions for cases where other object types are introduced. We also found that measures based on the size of Voronoi regions (of objects respective points) can be used for identifying different spatial distribution of information.

The next step in this ongoing study is to perform a case study with more object types and to study how these measures can be used to guide the generalisation process.

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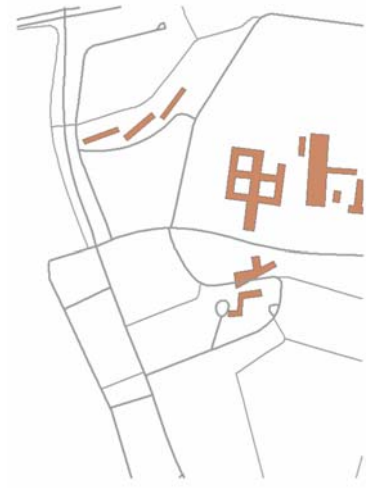
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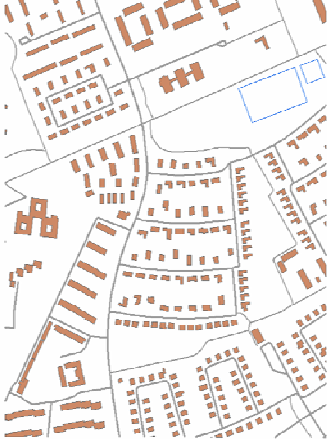





Appendix 1, Test Maps

The appendix shows the test maps used in the study. Seven different locations were used (I – VII). The maps (buildings) were then generalized to different extents using an algorithm developed and implemented by Hampe and Sester (2004). The algorithm simplified polygons by removing all features of a polygon that were shorter than a set parameter value. The generalization levels (1 – 5) correspond to:

1. The original geometry, which was suited for topographic maps of scale 1:10 000.
2. A building generalization; parameter value set to 4 meters.
3. A building generalization; parameter value set to 4 meters.
5. Only public buildings (with a generalization of 8 meters) presented.

		
Location I, generalization level 1	Location I, generalization level 3	
		
Location II, generalization level 1	Location II, generalization level 3	Location II, generalization level 5

		
Location III generalization level 1	Location III generalization level 2	Location III generalization level 3
		
Location IV, generalization level 1	Location IV, generalization level 2	Location IV, generalization level 3
		
Location V, generalization level 1	Location V, generalization level 2	Location V, generalization level 3

		
<p>Location VI, generalization level 1</p>	<p>Location VI, generalization level 3</p>	<p>Location VI, generalization level 5</p>
		
<p>Location VII, generalization level 1</p>	<p>Location VII, generalization level 3</p>	