# Analytical estimation of map legibility

H. Stigmar<sup>1</sup>, L. Harrie<sup>2</sup>, M. Djordjevic<sup>3</sup>

<sup>1</sup>National Land Survey of Sweden, S-801 82 Gävle, Sweden Email: hanna.stigmar@lantm.lth.se

<sup>2</sup>GIS Centre, Lund University, Sölvegatan 12, S-223 62 Lund, Sweden Email: lars.harrie@nateko.lu.se

<sup>3</sup>Geography Department, Faculty of Science and Mathematics, University of Nis, Visegradska 33, 18000 Nis, Serbia Email: milan.djordjevic@pmf.ni.ac.rs

# 1. Introduction

The possibility to combine and visualize information on the web stresses the importance of *map legibility*. Map legibility is here defined as a combination of *map readability* (discerning the symbols) and *map interpretation* (understanding the content of the map).

We have to establish better methods to improve the legibility of web maps. A key issue for this is to develop analytical measures of map legibility. The aim of this study is to establish such measures, and especially it aims at studying map legibility as a *synthesis of analytical measures*. In the study we evaluated three methods to perform syntheses: (1) threshold values, (2) linear index, and (3) non-linear index.

This extended abstract is a summary of the study. A more complete description of the study will, hopefully, be published as a full paper.

# 2. Methodology

#### 2.1 Framework

The framework of our study contains the following steps:

- (1) A number of map samples are created (section 2.2).
- (2) A user test is performed where the map samples are categorized into legibility classes (section 2.3).
- (3) Analytical measures are computed for each map sample (section 2.4).
- (4) Estimating map legibility using threshold values (section 2.5).
- (5) Estimating map legibility using linear index (section 2.6).
- (6) Estimating map legibility using non-linear index (section 2.7).

#### 2.2 Map samples

The map samples were derived from a geographic database over the vicinity of Helsingborg, Sweden, consisting of layers in the scale range  $1:10\ 000 - 1:50\ 000$ . First 60 map regions where selected; 30 regions dedicated to maps in scale of  $1:10\ 000$  and the others dedicated for maps in scale  $1:50\ 000$ . The maps for all 60 regions were compiled using three levels of detail (LOD 1-3) by selecting data layers of different resolutions. The maps were symbolized by two different symbologies (TS and NS).

In total we created 360 map samples (60 regions, 3 LOD, 2 symbologies) of the size 3x2 cm (see examples in Figure 1). 10 map samples were removed because of their close similarities with other map samples. That left us with a total number of 350 map samples for the user test.



Figure 1. Two map samples used in the study, one of type TS 50 LOD 1 (left), and one of type NS 10 LOD 2 (right).

## 2.3 User test of map legibility

The user test was designed as a web-distributed questionnaire. To be able to test all the 350 map samples without exhausting the participants, we developed seven tests with 50 map samples in each. The map samples were placed randomly in the tests. Apart from the different maps, the seven tests were identical. The tests were given in order as the participants opened the test web page (i.e. participant 1 was given test 1, participant 2 was given test 2, ..., participant 8 was given test 1, etc.). The test language was English, as we expected participants of different nationalities. In the test we used the term *readability* instead of *legibility*, as readability is easier to understand for people not so familiar with these terms, and who do not have English as their native language. The definition of readability given to the participants was:

Map readability is focused on the possibility to discern (separate them from each other and from the background) the map symbols, thus how easy it is to read the map, in order to interpret and comprehend it.

The test consisted of three parts; the only part described in this paper is the legibility evaluation part. This part consisted of 50 pages with one map sample on each page. On each page the participant was given the definition of "readability" and asked to estimate the "readability" of the map sample as: "very difficult to read", "difficult to read", "easy to read", or "very easy to read".

The legibility of the map samples was evaluated by persons with a map or GI background. The target user categories were: GIS and geography professionals, GIS and geography students, and people who use maps in their work (e.g. surveyors). The link to the test was e-mailed to the test persons. After removing some outliers, we got a total of 214 persons who participated in the test.

The answers given in the user test were collected and organized according to test task. The answers to the legibility evaluation were converted to numerical values of 1 to 4, corresponding to the legibility estimations made by the participants (1 for "very difficult to read", 2 for "difficult to read", etc.). For each map sample a mean value of the numerical conversions of the legibility estimations was computed; this value is denoted *perceived legibility value* below.

The maps where then classified as *legible* or *non-legible*. The maps with a perceived legibility value of less than 2.5 is regarded as non-legible; for those maps the test persons used the grade "very difficult to read" or "difficult to read" more frequently than "very easy to read" or "easy to read". The other maps were regarded to be legible. In total 110 maps were classified as non-legible and 240 as legible.

### 2.4 Computation of analytical measures

We have developed, implemented and evaluated the measures for map legibility that are listed in Table 1; some measures are our own, others are borrowed from e.g. Li and Huang (2002) and AGENT (1999). More details of some of the measures can be found in Harrie and Stigmar (2009) and Stigmar and Harrie (2010).

The measures can be subdivided into four measure types:

- *amount of information*, which is based on the amount and size of the map objects,
- *spatial distribution*, which is based on the density and distribution of the map objects,
- *object complexity*, which is based on the shape and size of the individual map objects, and
- graphical resolution, which is based on the symbolization of the objects.

The map objects, in their turn, can be subdivided into *information types* based on their geometrical properties (c.f. van Smaalen 2003, in Mackaness and Ruas 2007).

The measures were implemented in a Java program built on the open source packages *JTS Topology Suite* (JTS) and *JTS Unified Mapping Platform* (JUMP) (JUMP project 2009). In order to create Voronoi regions (used for evaluating the spatial distribution of points and objects) we use the c-program *Triangle* (Shewchuk 1996, 2002) integrated using Java native interface (Gordon 1998).

	Amount of information	Spatial distribution	Object complexity	Graphical resolution
Minor objects	<ul> <li>Number of objects</li> <li>Number of vertices</li> <li>Object line length</li> <li>Object area</li> </ul>	<ul> <li>Spatial distribution of objects</li> <li>Spatial distribution of vertices</li> <li>Number of neighbours</li> <li>Local density</li> <li>Semantic homogeneity</li> </ul>	<ul> <li>Object size</li> <li>Line segment length</li> <li>Angularity</li> <li>Polygon shape</li> </ul>	<ul> <li>Brightness difference</li> <li>Hue difference</li> </ul>
Line networks	<ul><li>Number of objects</li><li>Number of vertices</li><li>Object line length</li><li>Object area</li></ul>		<ul> <li>Line segment length</li> <li>Line connectivity</li> <li>Angularity</li> </ul>	<ul><li>Brightness difference</li><li>Hue difference</li></ul>
Tessellation objects	<ul><li>Number of objects</li><li>Number of vertices</li><li>Object line length</li></ul>	• Number of neighbours	<ul> <li>Object size</li> <li>Line segment length</li> <li>Angularity</li> <li>Polygon shape</li> </ul>	<ul><li>Brightness difference</li><li>Hue difference</li></ul>
Field-based data	<ul> <li>Number of objects</li> <li>Number of points in the objects</li> <li>Object line length</li> </ul>		<ul><li>Line segment length</li><li>Angularity</li></ul>	
All objects	<ul> <li>Number of object types</li> <li>Number of objects</li> <li>Number of vertices</li> <li>Object line length</li> <li>Object area</li> </ul>	<ul><li> Proximity indicator</li><li> Degree of overlap</li></ul>		

Table 1. A compilation of the measures and their application for the information types (rows) and measure types (columns).

#### 2.5 Estimating map legibility using threshold values

The aim of the evaluation described in this section was to develop a number of thresholds to be used in legibility guidelines. By manual inspection of scatter plots of measure values and perceived legibility classes for varying measures we obtained the thresholds for the following measures:

- number of object types
- number of objects (for area tessellations)
- object line length (for area tessellations)
- object line length (for continuous fields)
- object line length (for all objects)
- number of vertices (for continuous fields)
- number of vertices (for all objects)
- proximity indicators
- degree of overlap (for disjoint objects)
- angularity (maximal)

We then defined a legible map as a map that holds all of these thresholds. By using Matlab we classified all the maps (of TS symbology) as legible or not. Finally, this classification was compared to the perceived legibility.

The result revealed 85% percent correct classified map samples. With the threshold values we were able to correctly capture 36 of the 49 non-legible maps. However, 14 of the 126 perceived legible maps were also categorized as non-legible.

### 2.6 Estimating map legibility using linear index

A linear index for map legibility is defined as:

$$linear\_legibility\_index = \alpha + \beta_1 \cdot m_1 + \beta_2 \cdot m_2 + \dots + \beta_n \cdot m_n$$
(1)

where

 $\alpha$ ,  $\beta_i$  are parameters,  $m_i$  is the value for measure *i*, *n* is the number of measures used in the index.

To determine the parameters values in our study we used a multiple linear regression (based on a least square fit).

The main challenge for creating a linear index is to decide which measures that should be included. If too few measures are used, the risk is that essential properties of the map legibility are not considered. On the other hand, if too many measures are used the risk is that values for a less significant measure will negatively affect the result.

In the study we used 175 maps of the TS symbology. 145 of those map samples where used to determine the parameters in Equation (1). The remaining 30 test maps were used for evaluation. For those 30 maps we computed the linear legibility index (Equation 1) using the measures:

 $m_1$  = Number of vertices (all objects)

 $m_2$  = Number of object types (all objects)

 $m_3$  = Degree of overlap for disjoint objects (all objects)

 $m_4$  = Brightness difference (tessellation objects)

 $m_5$  = Object size - 30% limit (minor objects)

If the linear index was less than 2.5 we classified the map as non-legible, otherwise it was classified as legible.

Finally, a comparison was made between the estimated legibility from the index with the perceived legibility. The result revealed 81% correct classified map samples.

#### 2.6 Estimating map legibility using non-linear index

The non-linear index can symbolically be written as:

$$non\_linear\_legibility\_index = f(m_1, m_2, ..., m_n)$$
(2)

The key issues here are to determine which measures to use and to establish the non-linear relationship (f) between the measures and the legibility index.

In our studies we established this relationship using an artificial neural network called Fuzzy ARTMAP (Carpenter et al., 1992) (which is a supervised learning technique). In a simplified view we use Fuzzy ARTMAP as follows. First all the map samples are divided into training and test map samples. Then, the network is trained using the training map samples (Figure 2). The measure values for these samples are provided to an ARTa module. This module then performs unsupervised learning to create some categories of the map samples. Via the map field and the ARTb module these categories are linked to the perceived legibility classes for training map samples (i.e., supervised learning). In this learning phase the neurons in ARTa and ARTb are trained for the input data.

In the classifying phase we use the measure values for the test maps as input to Biased ARTMAP (Figure 3). As output from the network we receive estimated legibility classes. These classes are then compared with the perceived legibility classes for the test map samples by confusion matrixes and quality measures.



Figure 2. ARTMAP learning phase.



Figure 3. ARTMAP classifying phase.

In the study we used 175 maps of the TS symbology. 145 of those map samples where used to train the network; the remaining 30 test maps were used for evaluation. We used the same attributes as for the linear indexes.

By running the test maps in Fuzzy ARTMAP (according to Figure 3), we obtained a classification whether the map was estimated to be legible or not. This classification was then compared to the perceived legibility from the user studies for those map examples. The result revealed 81% correct classified map samples.

# 3. Discussion

This study revealed that it is possible to make an estimation of map legibility based on a synthesis of legibility measures. Even though the estimations are not perfect they could be useful from a pragmatic point of view, for example for triggering, controlling and assessing generalization processes.

We are still evaluating the synthesis methods. Preliminary we would state that: simplest is the best. Using threshold values is a simple method that provides a useful result. The distribution of measure values does not fit computations of linear indexes using multiple regression; so if linear indexes are going to be used, then other computational methods should be investigated. Even though fuzzy ARTMAP has some appealing features we have not obtained enough good results with the method. This might be due to too few map samples, or simply that the distribution of measure values does not fit this supervised learning technique. However, the main limitation of our approach is probably the measures. There is a lack of measures that describe important map legibility aspects. If we aim at really estimating map legibility analytically, which we believe is necessary in the future, then we as a community has to put more effort in defining map legibility measures.

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