Development of a Semantic Segmentation Approach to Old-Map Comparison

Yves Annanias
Image and Signal Processing Group, Leipzig University, Germany

Daniel Wiegreffe
Image and Signal Processing Group, Leipzig University, Germany

Andreas Niekler
Computational Humanities, Leipzig University, Germany

Marta Kuźma
Faculty of History, University of Warsaw, Poland

Francis Harvey
Leibniz Institute for Regional Geography, Leipzig, Germany
Faculty of History, University of Warsaw, Poland

Abstract

This paper describes an innovative computational approach for comparing old maps. Maps older than 20 years remain a vast treasure of geographic information in many parts of the world with potential applications in many environmental and social analyses, e.g., establishing road construction over the past 80 years or identifying settlement growth since the middle ages. Semantic segmentation has developed into a viable computational method for analysing old maps from previous centuries. It allows for the discrete identification of elements, e.g., lakes, forests, and roads, from cartographic sources and their computational modelling. Semantic segmentation uses convolutional neural networks to extract elements. With this technique, we create a computational approach to compare old maps systematically and efficiently.

2012 ACM Subject Classification Human-centered computing → Interactive systems and tools; Information systems → Geographic information systems

Keywords and phrases Geographic/Geospatial Visualization, Visual Knowledge Discovery, Cartographic Analysis

Digital Object Identifier 10.4230/LIPIcs.GIScience.2023.14

Category Short Paper

Funding *Marta Kuźma and Francis Harvey:* The project is co-financed by the Polish National Agency for Academic Exchange within the NAWA Chair programme.
Yves Annanias: This research was supported by the Development Bank of Saxony (SAB) under Grant 100400221.

1 Introduction

Semantic segmentation is a computational method for analyzing old maps from previous centuries, allowing for discrete identification of elements like lakes, forests, and roads. This technique uses convolutional neural networks to extract the elements. The old maps used in this process contain valuable information, and comparing the elements they contain supports numerous environmental and social applications. Here, we present an innovative approach that allows us to compare multiple old maps. The paper considers the concepts and implementation and includes an assessment of the results of the new approach. Particularly challenging for this historical, geographical analysis are scale-related differences, distortions

12th International Conference on Geographic Information Science (GIScience 2023).
Editors: Roger Beecham, Jed A. Long, Dianna Smith, Qunshan Zhao, and Sarah Wise; Article No. 14; pp. 14:1–14:6
Leibniz International Proceedings in Informatics
LIPICS Schloss Dagstuhl – Leibniz-Zentrum für Informatik, Dagstuhl Publishing, Germany

of old map sheets, undocumented projection parameters and cartographic generalisation effects. The parametrisation of the semantic segmentation can take some geometric issues into account.

Our approach advances the handling of cartographic dimensions and will make systematic comparisons of collections of old maps possible and viable for the first time. For this, we construct a quadtree-based data structure that divides a map section and the features it contains into smaller and smaller sections, grouping them together. By visually displaying the levels of the quadtree as a heatmap, we then enable a more targeted comparison of features of the maps. Whereby the color coding highlights interesting map sections that may be of interest for a comparison. For the accurate and efficient modelling of the information from the old maps, we rely on a graph database that improves computational efficiencies of the cartographic element extraction and comparisons. In the paper, we document the modelling, processing and spatial visual comparisons of results of exemplary maps from the early and mid-twentieth centuries. The assessment of results points to challenges we are taking up in ongoing research.

2 Semantic Segmentation of Old Maps

Creating geographic information from old maps is an important source of data for many applications. For example, Uhl et al. [15] describe potentials for the over 200,000 topographic map sheets of the USGS map archive. While scanned versions of old maps are useful for wall hangings, screen savers and visual analysis by themselves, spatial analytical approaches frequently require additional processing to transform coordinate systems or features for specific project requirements. The transformation from raster to vector allows for other analytical operations that are well known from the development of GIS [5]. The cartographic modelling and geo-relational basis of those spatial analysis techniques is suitable for specific application and is limited by the computation complexity [14]. Database approaches are additionally advantageous when data can be optimised for requisite storage schemes and applications [4]. Machine learning approaches have for some years offered further computational improvements such as in [3] and are well-suited for the increasingly available large amounts of rasterised or vectorised geographic information.

2.1 Addressing cartographic challenges

Scale, distortions of old map sheets, undocumented projection parameters and cartographic generalisation effects are very significant challenges for any comparisons of old maps. Cartographic approaches, which stress graphic variables, concepts from cartographic design and features, build on traditional concepts of map representation that contemporary geographic information modelling approaches can never fully reconstruct [11]. The documented and archival information is usually very incomplete and research to gain insights involves much work and often only partial clarity. This can guide different modelling attempts. Often assumptions are made [13]. Old maps often are visually very insightful and intriguing documents of past geographical situations and relationships [17, 9]. Their accuracy is frequently limited and poses great challenges. In work using geographic information systems, the challenges are well known [8]. In cartography, research involves maps and specialised literature [6]. Their resolution is very time consuming. Integration of historical maps involves complicated and demanding data preparation and error mitigation [10]. We draw on these lessons and harness the capabilities of geographic information processing in our computational modelling. The computational approach in this research attempts to compare historical maps, which computational approaches can greatly enhance help researchers move beyond the cartographic feature concept through the semantic segmentation process. The difference in terms stresses that the approach we describe here is information modelling approach to working with old maps.

3 Semantic segmentation for old map comparison

A critical part of working with old maps is determining the parameters for transforming digital raster scans of old maps into vector representations, suitable for CNN and normalisation of the coordinates for numerical pattern matching. Work on large-scale image analysis points the way for the approach we are developing. Therefore, we require a thorough documentation of processing steps and geometric attributes to allow for later assessments of comparison results including the identification of limitations arising from scale, distortions projections, or cartographic generalisation. Several researchers have addressed these issues [12, 15, 16, 18].

There are a variety of visualisations for geospatial and temporal data using a geographic information system (GIS). Andrienko et al. [1] provide a list of visualization-based techniques that allow the exploratory analysis of this kind of data. Since visual comparisons are essential in this task, we follow the guidelines of Gleicher [7]. In addition, as scalability also has an impact, we use the described strategy of *summarize somehow*. For this purpose, we rely for our approach on *explicit encoding*, whereby relationships between elements are visualised.

3.1 Process overview

Our approach follows the process presented in 2022 by Annanias et al. [2], but is simplified by limiting the area we consider in this pilot study, which focuses on a limited range of map element types and a small area. We adapted the color scheme, to fit to the new use case. The original version is used to aggregate data and show the distribution of that data over a larger area. With the limited map elements, it is now used to point out differences of similar elements. The parts of the the process are:

1. Implement shape comparisons between polygons in two maps using Hausdorff or Frechet distances and provide a system to support discovery and queries AND
2. Implement a GUI to compare multiple old maps by feature types or areas relying on visual opacity to support interactive visual inquiry.

3.2 Linking visual elements for further processing

The two parts of the process can be technically summarised as a five step sequence, whereby a quadtree-based data structure is created:

1. Determine the bounding box over all features, use it as the first parent cell.
2. Link all features to this parent cell.
3. Divide this cell into 4 equal parts (child cells).
4. Link all features from the parent cell to the child cell if they overlap with the child cell.
5. For each child cell, the process is repeated from step 3.

This process breaks the map image down and creates a quadtree, which consists of a grid of adjacent cells on each level (see Figure 1). As cells become smaller and therefore cover smaller areas of the map, the number of intersection calculations per cell becomes less. As a result, the test against the feature set of the parent cell becomes more computationally efficient. The number of cells, on the other hand, increases strongly. This information and all relationships are then stored efficiently and flexibly in a graph database. Each cell and

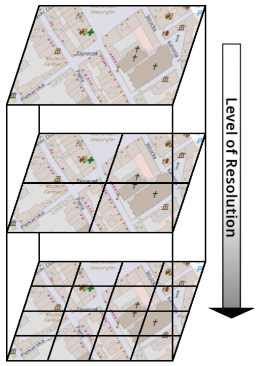

Figure 1 From top to bottom: The initial map is divided progressively into equal parts, thus creating a quadtree with different resolution levels.

feature are represented by nodes connected by edges where the cell overlaps the feature. Cell nodes are also connected with each other by edges to represent the structure of the quadtree. In this way, the information for a grid level can be queried flexibly and the size of the overall graph becomes less important. At the most detailed grid resolution, only features that have a strong geographical adjacency are grouped together. At the lower levels of resolution, proximity in the quadtree is more diffuse and has a decreasing significance (e.g., a feature in one corner of a cell may have absolutely nothing to do with a feature in another corner of the same cell). Therefore, features that are too far apart no longer interact with each other. Because the process stops before reaching the next resolution level earlier, it avoids the extreme case, where each cell on the lowest level corresponds to only one piece of a feature (equivalent to perfect overlapping of two features) as the main task is not to find perfect overlaps of features. However, since offsets are also omitted and slight shifts of the features in relation to each other are no longer recorded, the process stops earlier after the 9th level. A cell on the lowest level has a resolution of about $1m^2$ in this study.

After the processing, each level of the quadtree can be used for visualisation. For this purpose, a level consisting of a grid of cells is represented as a heatmap in a GIS. So the heatmap is an aggregated representation of overlapping features (*summarize somehow*). Each cell of this heatmap is colored according to the relationships of the features that are linked to this cell (*explicit encoding*).

4 Results

The result is shown in Figure 2. Features from an old digitised map from 1941/1942 (blue) were used with OSM data (red), which are displayed superimposed in a). It is clearly visible that both feature categories overlap with each other. However, this overlap prevents us from seeing exactly how they overlap everywhere, as one obscures the other too much. So it is also important which category is displayed on top of which other. Similarly, if there are only small differences in detail, it is necessary to zoom in very close to see them, otherwise they may be overlooked. Figure 2 b) uses the same data, but uses a level from the quadtree and displays it as a heatmap (the previously created cells). The quadtree level with the highest resolution determines the color of a cell. Yellow cells indicate whether there are features from both categories within the cell. Cells of lower resolution levels inherit the color yellow if at least one of the four child cells is also marked yellow. This ensures that the features of both categories within a cell have a spatial proximity.

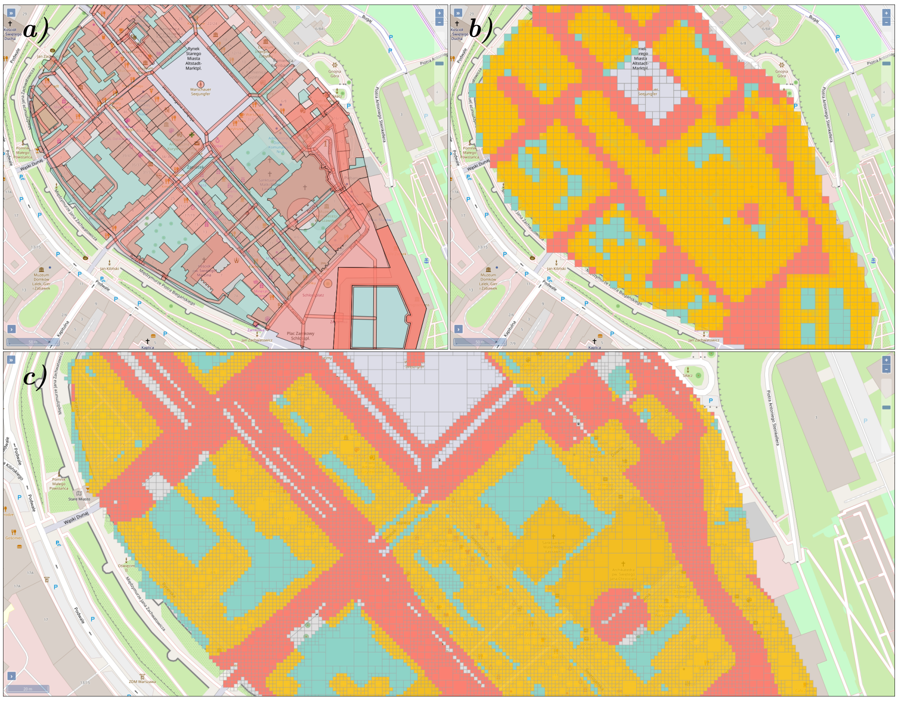

Figure 2 a) Features of two maps are shown. b, c) Two resolution levels of the quadtree displayed as a heatmap (coarse to fine). Red (blue) cells contain only OSM (1941/1942) data features, and yellow cells contain at least one feature from both categories. White cells do not contain any features.

Using this visualization, it no longer matters which category is on top of the other, as the aggregated information for the cell is displayed. Similarly, subtle differences can no longer be overlooked. However, this is still a rough representation of the overlap and serves as a simple indication of areas of interest. This overview can be used, for example, to identify regions of interest in larger map segments. In doing so, a user can locate sub-areas through the larger grid cells, which can be viewed in detail by zooming and panning in the next step. c) shows the heatmap at a finer level of resolution. There is more detail here and it is easier to see where the features overlap and where they do not.

This allows the differences to be examined more closely without the visual clutter caused by the overlaps themselves. This representation thus serves as a starting point for the precise analysis of the shift of the categories towards each other. The comparison results support the visual comparison in a novel way that extends capabilities. Through an iteration of parameters, the resulting 'information spaces' extend canonical cartographic presentations to help researchers gain new insights into changes between two maps, for example assessing when a city's medieval walls were built up or torn down at various parts of a city.

5 Summary

In this paper, we present an innovative computational approach applied for comparing old maps. Showing good potential for historical research, the process has potential as well in other areas, e.g., assessments of urban development over the past 80 years or identifying ancient settlement growth. This preliminary result and other projects show that semantic segmentation is a viable computational method for the analysis of digitised old maps. This paper presents the computational process to compare old maps systematically and efficiently. Future research considers how to more fully automate the process and the comparisons.

References

1 Natalia Andrienko, Gennady Andrienko, and Peter Gatalsky. Exploratory spatio-temporal visualization: an analytical review. *Journal of Visual Languages & Computing*, 14(6):503–541, December 2003. doi:10.1016/S1045-926X(03)00046-6.

2 Yves Annanias, Dirk Zeckzer, Gerik Scheuermann, and Daniel Wiegreffe. An interactive decision support system for land reuse tasks. *IEEE Computer Graphics and Applications*, 42(6):72–83, 2022. doi:10.1109/MCG.2022.3175604.

3 Nicolas Audebert, Bertrand Le Saux, and Sébastien Lefèvre. Semantic segmentation of earth observation data using multimodal and multi-scale deep networks. In *Computer Vision–ACCV 2016: 13th Asian Conference on Computer Vision, Taipei, Taiwan, November 20-24, 2016, Revised Selected Papers, Part I 13*, pages 180–196. Springer, 2017.

4 Prafullata Auradkar, Tejas Prashanth, Suraj Aralihalli, Sreeniketh Pradeep Kumar, and Dinkar Sitaram. Performance tuning analysis of spatial operations on spatial hadoop cluster with ssd. *Procedia Computer Science*, 167:2253–2266, 2020.

5 Nicholas R. Chrisman. Design of geographic information systems based on social and cultural goals. *Photogrammetric Engineering and Remote Sensing*, 53(10):1367–1370, 1987.

6 Matthew Edney. *Cartography. The ideal and its history.* University of Chicago Press, Chicago, 2019.

7 M. Gleicher. Considerations for Visualizing Comparison. *IEEE Transactions on Visualization and Computer Graphics*, 24(1):413–423, 2018. doi:10.1109/TVCG.2017.2744199.

8 Bernard Jenny, Helen Jenny, and Lorenz Hurni. Alte Karten als historische Quelle – Wie lässt sich die geometrische Genauigkeit des Karteninhalts abschätzen? In C. Koller and P. Jucker-Kupper, editors, *Karten, Kartographie und Geschichte – Von der Visualisierung der Macht zur Macht der Visualisierung / Cartes, cartographie et Histoire – De la visualisation du pouvoir au pouvoir de la visualisation*, pages 127–144. Chronos Verlag, Zürich, 2009.

9 Anne Kelly. Knowles and Amy Hillier. *Placing history : how maps, spatial data, and GIS are changing historical scholarship.* ESRI Press, Redlands, Calif., 2008.

10 J.B. Owens, May Yuan, M. Wachowicz, Vitit Kantabutra, E.A. Coppola, Daniel Ames, and Aldo Gangemi. Visualizing historical narratives: geographically-integrated history and dynamics gis. *library.wur.nl*, 2009.

11 Tomasz Panecki. Digital methods in cartographic source editing. *Digital scholarship in the humanities*, 36(3):682–697, 2020.

12 Rémi Guillaume Petitpierre, Frédéric Kaplan, and Isabella Di Lenardo. Generic semantic segmentation of historical maps. *CEUR Workshop Proceedings*, 2989(27):21. 228–248, 2021.

13 Stanisław Pietiewicz. Analyse de l'exactitude de quelques cartes du xviie, xviiie et xixe siècle, couvrant les territoires de l'ancienne pologne. *Przegląd Geograficzny*, Special Issue for the XIX-th International Geographical Congress, Stockholm 1960:21–27, 1960.

14 Shashi Shekhar and Sanjay Chawla. *Spatial Databases. A Tour.* Pearson Education Inc., Upper Saddle River, NJ, 2003.

15 Johannes H Uhl, Stefan Leyk, Yao-Yi Chiang, Weiwei Duan, and Craig A Knoblock. Map archive mining: visual-analytical approaches to explore large historical map collections. *ISPRS international journal of geo-information*, 7(4):148–167, 2018.

16 Johannes H Uhl, Stefan Leyk, Yao-Yi Chiang, Weiwei Duan, and Craig A Knoblock. Automated extraction of human settlement patterns from historical topographic map series using weakly supervised convolutional neural networks. *IEEE Access*, 8:6978–6996, 2019.

17 M Wachowicz and JB Owens. The role of knowledge spaces in geographically-oriented history. *History and GIS*, 2013.

18 Kun Zheng, Ming Hui Xie, Jin Biao Zhang, Juan Xie, and Shu Hao Xia. A knowledge representation model based on the geographic spatiotemporal process. *International Journal of Geographical Information Science*, 36(4):674–691, 2022.