Automatic Vectorization Of Urban Structures In Historical Maps

By Elisa Farella, Salim Malek, Fabio Remondino

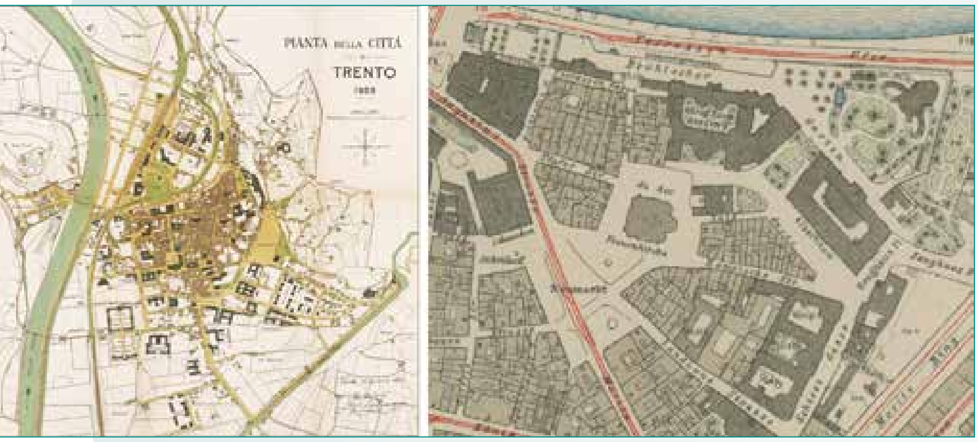

Fig. 1 - Example of different historical maps from Trento (Italy) and Dresden (Germany).

Historical urban maps are an unvaluable source for many geospatial and heritage applications. Vectorialization of such historical contents by means of learning-based techniques is really promising and opening many prospectives.

Historical maps, stored in various archives and being digitized around the globe, are offering valuable insights into the transformation and development of past urban landscapes. The different graphical styles and drawing methods used in map creation reflect distinct communication goals and cultural identities. Today, these important documents are recognized as heritage assets, requiring preservation both physically, to prevent deterioration over time, and digitally, to protect their content. The growing availability of digitized historical maps, along with increasingly advanced digital tools and algorithms, opens up new possibilities for their usage and applications.

Recent research in processing historical maps focus on two main aspects:

1) geo-referencing of digital maps for their integration within GIS environments (Duan et al., 2020; Luft.and Schiewe, 2020; Craciun and Le Bris, 2022)

2) vectorization of map features like buildings and streets (Iosifescu et al., 2016; Chrysovalantis and Nikolaos, 2020; Heitzler and Hurni, 2020; Le Riche, 2020; Petitpierre and Guhennec, 2023; Chen et al., 2024).

While the former is almost automatized, the vectorization task is currently a manual and time-consuming process: its automation can broaden data applications (e.g. visualization, 3D building modeling, change detection, etc.), besides ensuring the preservation of their content. Additionally, enriching vector data with attributes can support the analysis and interpretation of urban changes using GIS tools, enabling the computation of building spatial distribution, the identification of patterns, and the evaluation of relationship between urban and natural elements.
At FBK we have developed a new methodology for the automatic vectorization of buildings in historical maps. The solution is based on Artificial Intelligence (AI) and combined with image processing and GIS functions for optimizing the prediction results and vector data creation.

Methodology

The implemented process relies on two main steps: (i) semantic segmentation with a deep learning network and (ii) optimization through image processing techniques. For the first task, the DeepLabV3, an optimized version of the DeepLab (Chen et al., 2017), is exploited to train the model. The backbone architecture is

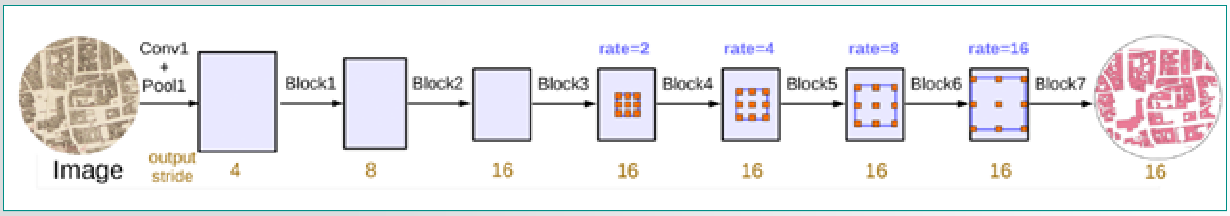

Fig. 2 - The DeepLabV3 neural network exploited for buildings' segmentation.

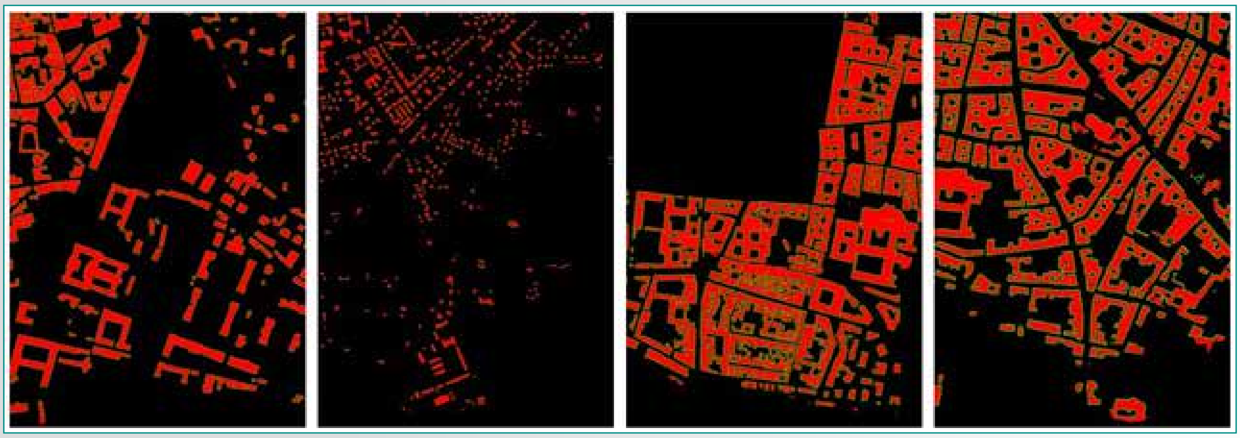

Fig. 3 - Segmentation results (raster) derived using the DeepLabV3 network.

based on ResNet101 (He et al., 2016), which introduces the concept of atrous, a dilatated convolution for capturing a more comprehensive image context during the learning without reducing its resolution.

The post-processing of the predicted segmented map (raster) involves the use of several image-processing techniques to improve the segmentation results before polygonizing the building footprints. In particular, a Connected Component Analysis (CCA) is used to remove small components (such as isolated lines and small objects), while a skeletonization algorithm followed by a morphological dilatation is applied to improve the buildings' border. At this stage, the quality of the polygonized data is defined by the correct number of vertices to reconstruct the polygons from the raster. Therefore an adaptive threshold, computed as the Intersection of the Union (IoU) of several threshold values (95%), is applied. Finally, the polygons are optimized by removing spaces or overlaps among adjacent features.

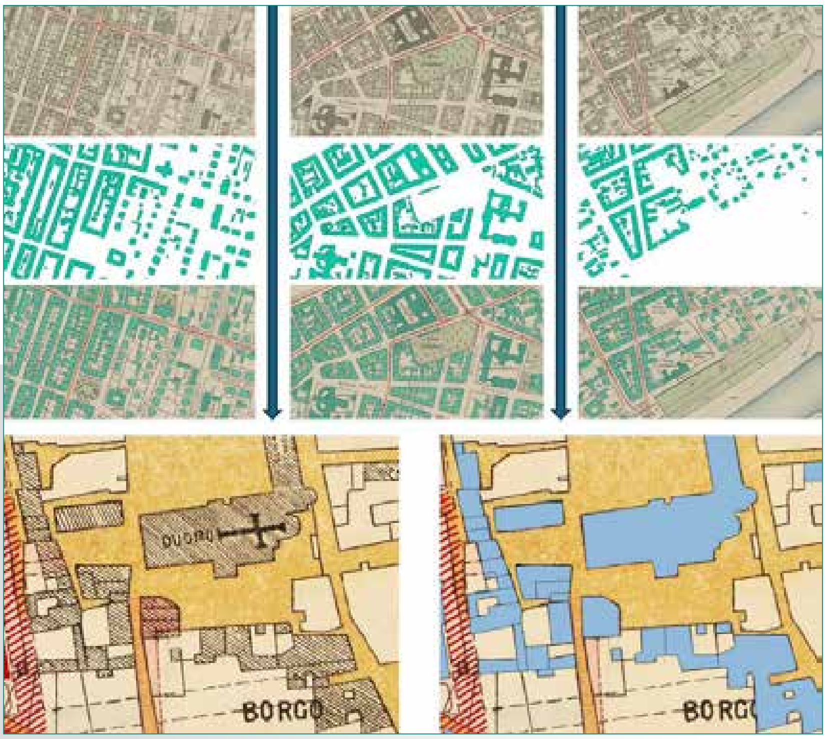

Fig. 4 - Examples of the final vector building footprints from historical maps.

Results and generalization

The implemented vectorization procedure was applied to various types of historical urban map, especially topographic ones, where urban settlements and building footprints are clearly distinguishable.

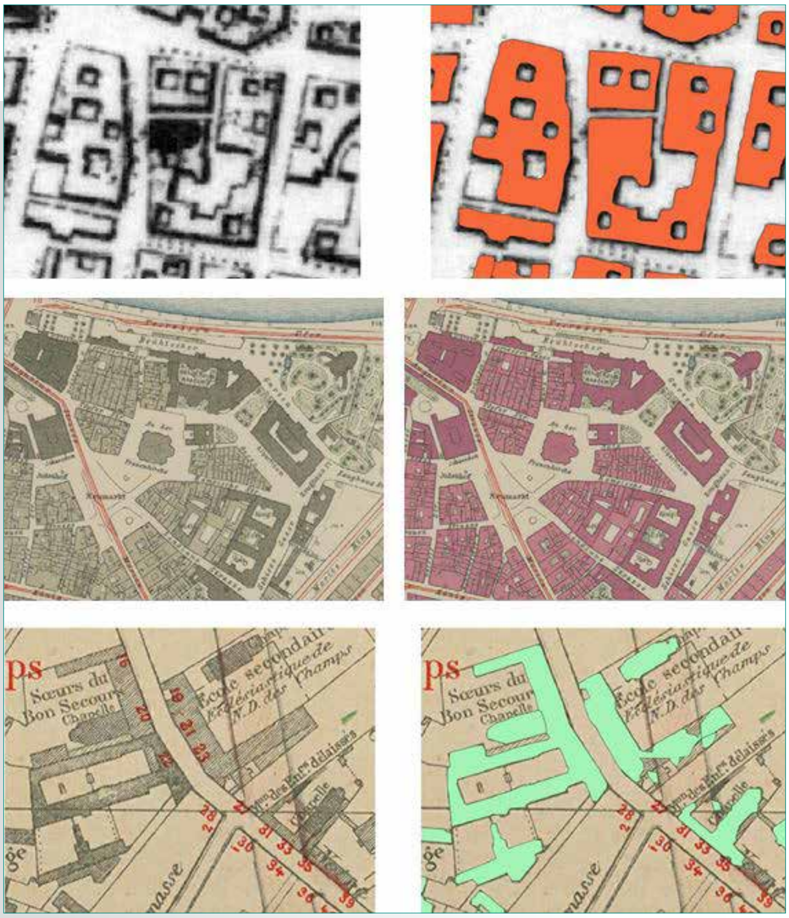

Fig. 5 - Further results of generalization tests for maps of Bologna (Italy), Dresden (Germany) and Paris (France).

The AI-based procedure was trained using data from seven manually segmented and annotated city maps representing three different locations: Trento, Italy (four maps from 1851 to 1936), Bologna, Italy (1884, 1945) and Dresden, Germany (1911). These same maps were used to verify the prediction capabilities of the AI neural network, using a portion of the manually digitized polygons as training data and evaluating the predictions on the evaluation and test sets. The variety in drawing style across these maps makes generalization of the models more challenging. The similarity between training data and the map to predict influences the model's performance, so fine-tuning with additional training data could be needed.
Results (Figure 4-5) are promising and open-up many possibilities for using such vector information in many applications (4D city modeling – Figure 6, change detection, etc.).

Discussion

The findings highlight the significance of the post-processing and refinement stage following AI-based predictions in enhancing the quality of the final vector data. The experiments demonstrate the proposed method's ability to streamline a typically manual and time-intensive process. This solution shows great potential for preserving the digital content of historical maps while expanding our understanding of urban contents and changes. Generalization capabilities to unseen scenarios (e.g. Paris, Figure 5) are promising although the different drawing styles reduce the performances of prediction capabilities.
DIDA: Fig. 5 - Further results of generalization tests for maps of Bologna (Italy), Dresden (Germany) and Paris (France).
DIDA: Fig. 6 - Use of vectorialized historical maps for the creation of 4D city models (Farella et al., 2021).

Fig. 6 - Use of vectorialized historical maps for the creation of 4D city models (Farella et al., 2021).

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KEYWORDS

Cartography; Historical Maps; GIS; Automatic vectorialization; AI solutions; geometric data;

ABSTRACT

For the most diverse practical purposes and communication needs (from trade to conquests or exploratory voyages), man has always represented space through the production of maps. There are countless varieties of themes, styles and graphic languages, types of representation (pictorial maps, bird's eye views, cadastral and topographic maps) used throughout history to depict, in particular, the landscape and the urban fabric. The informative, historical, cultural and identity value of this cartographic heritage, now preserved in archives and institutions around the world, is inestimable. Due to the need to preserve its content from the ravages of time and to allow its "digital" use, an increasingly intense campaign of digitization of these sources has been launched in recent years (as has happened, for example, for other historical data, such as photographs and books). The growing availability of digital historical maps and, at the same time, the notable progress in data processing and analysis, today offers new perspectives for the use and valorization of these resources. In the case, in particular, of ancient cartography, there are increasingly broader scenarios for accurate studies on the evolution and transformation of urban structures, to support careful urban planning policies or reconstruct historical scenarios (Farella et al., 2021).

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