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Deep learning for map generalization: Experimenting with coastline data at different map scales

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Abstract:

Traditionally, map generalization is a vector-based process which is based on the implementation of various geometric operators utilized to produce geospatial data from a larger to a smaller map scale. Among the existing approaches to map generalization, line simplification constitutes a filtering process which selects the critical points to be transferred from the initial to the generalized cartographic line (Jiang and Nakos, 2003). Over the last decades, well-established algorithms for line simplification have been incorporated into both commercial and open-source GIS software, substantially supporting the process of cartographic production in different types of map agencies. However, considering that map generalization refers to a graphical problem and that it is difficult to model the cartographer's decisions during the generalization of a cartographic product (Touya et al., 2019), the application of deep learning techniques seems to be quite promising for the existing need to provide automated map generalization processes (Zhang et al., 2024). Indeed, deep learning techniques have been applied for the generalization of relief shading, contour lines, coastlines (e.g., Jenny et al., 2022), buildings (e.g., Sester et al., 2018), as well as map tiles (Courtial et al., 2024).

In the present study, we present a deep neural network approach towards cartographic line generalization. In particular, we use vector coastline data at different scales, adapted from Eurostat (European Commission). The vector data are properly transformed into raster in order to generate a concrete dataset for training the neural network. The input of the neural network consists of raster image samples originating from a larger scale (initial lines) while the output contains the corresponding samples in a smaller scale (generalized lines). Specifically, for each vertex of the larger scale, a raster image sample is generated in both the larger and smaller scales using a window of user-defined dimensions centered on the vertex. In this way, a training sample pair is created for each vertex, where the input and the desired response are given by the corresponding images. The training data may be further augmented by geometric transformations such as rotation and reflection. For example, a 1:1 million map under consideration provides 12K sample images that raise up to 100K when augmentation is applied. This process results in a large amount of training data which serves as input to train a U-Net deep neural network. Such networks are known to perform well on image-to-image problems (Ronneberger et al., 2015; Feng et al., 2019). The proposed U-Net architecture consists of 57 layers and a total of 31M learnable parameters.

During evaluation a test vector map at a larger scale undergoes the described workflow of generating raster samples that feed the network in order to extract the corresponding smaller scale raster samples. These individual samples are fused in a post-processing step where only the statistically most probable pixels are selected in order to construct the final generalized map. Specifically, a percentage threshold is applied to the cumulative density distribution of pixel intensities. Figure 1 depicts the basic steps of the evaluation process in an example area (all images are shown color inverted for visualization purposes). Both input and output raster samples are indicated by blue squares. The network's predictions are spatially fused and pixels with statistically higher contribution are isolated in order to produce the final output image map. The proposed method has been tested in various combinations of three different map scales, including 1:1 million, 1:3 million, and 1:10 million. As shown in the top row of Figure 1, in case of samples positioned on the vertices of the input larger scale map the proposed method achieves an average boundary F-measure (Csurka et al., 2013) of 94%. The experimental results indicate that the generalization efficiency is higher in areas where the output samples are dense. The bottom row of Figure 1 depicts an alternative approach where (non-empty) samples are generated in a grid-based mode. Covering the examined area with samples characterized by uniform spatial distribution leads to an even higher value of the boundary F-measure (~97%). Future work includes the further investigation of alternative sample positioning strategies using specialized tools (e.g., Kesidis et al., 2022).

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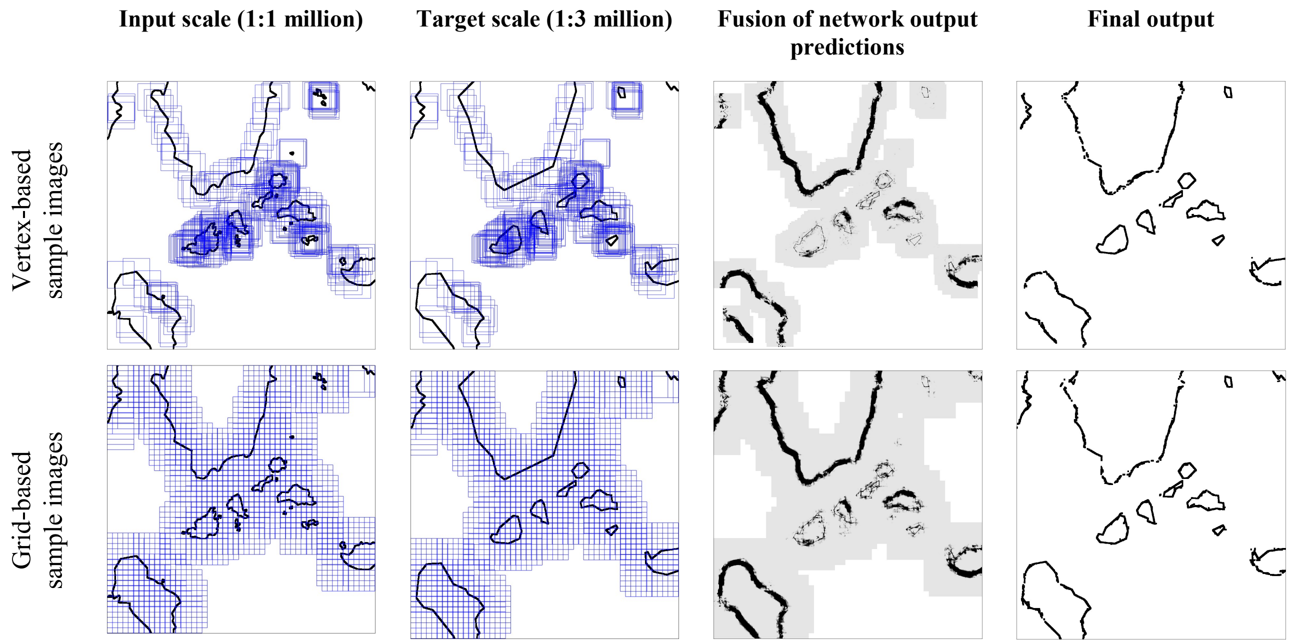

Figure 1. Example of 1:1 million to 1:3 million scale generalization. The top and bottom row demonstrate a vertex-based and grid-based approach, respectively, for the generation of sample images.

References

Courtial, A., Touya, G., & Zhang, X. (2024). DeepMapScaler: a workflow of deep neural networks for the generation of generalised maps. *Cartography and Geographic Information Science*, 51(1), 41–59. https://doi.org/10.1080/15230406.2023.2267419

Csurka, G., D. Larlus, and F. Perronnin. (2013) What is a good evaluation measure for semantic segmentation? In: *Proc., British Machine Vision Conference*, Bristol, UK.

Feng, Y., Thiemann, F., & Sester, M. (2019). Learning Cartographic Building Generalization with Deep Convolutional Neural Networks. *ISPRS International Journal of Geo-Information*, 8(6). https://doi.org/10.3390/ijgi8060258

Jenny, B., Singh, D., Walker, B., Patterson, T., Heitzler, M., Farmakis-Serebryakova, M., Hurni, L., & Samsonov, T. (2022). Neural networks for generalized relief shading, contour lines and coastlines. In: *Proc., 4th International Research Symposium on Cartography and GIScience (AutoCarto 2022)*, Redlands, California.

Jiang, B., & Nakos, B. (2003). Simplification Using Self-organizing Maps. In: *Proc., ISPRS Workshop on Spatial Analysis and Decision Making*, Hong Kong.

Kesidis, A. L., Krassanakis, V., Misthos, L.-M., & Merlemis, N. (2022). patchIT: A Multipurpose Patch Creation Tool for Image Processing Applications. *Multimodal Technologies and Interaction*, 6(12). https://doi.org/10.3390/mti6120111

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. In N. Navab, J. Hornegger, W. M. Wells, & A. F. Frangi (Eds.), *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015* (pp. 234–241). Springer International Publishing.

Sester, M., Feng, Y., & Thiemann, F. (2018). Building generalization using deep learning. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLII–4, 565–572. https://doi.org/10.5194/isprs-archives-XLII-4-565-2018

Touya, G., Zhang, X., & Lokhat, I. (2019). Is deep learning the new agent for map generalization? *International Journal of Cartography*, 5(2–3), 142–157. https://doi.org/10.1080/23729333.2019.1613071

Zhang, X., Touya, G., & Meijers, M. (2024). Automated Map Generalization: Emerging Techniques and New Trends (Editorial). *Journal of Geovisualization and Spatial Analysis*, 8(1), 11. https://doi.org/10.1007/s41651-024-00174-4

https://doi.org/10.5194/ica-abs-7-180-2024 |