NEURAL NETWORKS FOR GENERALIZED RELIEF SHADING, CONTOUR LINES AND COASTLINES

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Introduction

Artificial neural networks excel at analysing and transforming images and other raster fields. We apply U-nets, a type of convolutional neural network (Ronneberger et al., 2015) to cartographic generalization problems. We discuss three applications to derive generalized terrain representations from geospatial raster data (Guilbert et al., 2014). In the first application, we create generalized shaded relief; the neural network directly derives shaded relief images from digital elevation models. In the second application, we create generalized contour lines; the neural network generalizes the digital elevation model source to an intermediate elevation model, and generalized vector contour lines are derived from this intermediated elevation model with a contouring algorithm. In the third application, we create generalized coastlines with a neural network from a raster field that encodes the occurrence of surface water. The network produces a black-and-white coastline image, attuned to the continental landmasses and islands, which are then delineated as vector lines. We observe that high-quality reference data is required for training neural networks, and identify two complementary approaches to control the amount of generalization with neural networks that apply to the three described applications.

Neural Networks for Generalized Relief Shading

Neural networks successfully replicate the generation of hand-drawn shaded relief (Jenny et al., 2021). The neural networks are trained with (a) manual shaded relief images and (b) terrain models of the same area. The neural networks are able to generate shaded relief that closely resembles hand-drawn shaded relief art. The neural networks follow essential design principles of manual relief shading, such as removing unnecessary terrain details, locally adjusting the illumination direction, accentuating high peaks with aerial perspective, and emphasizing large landforms.

There are two complementary generalization methods for relief shading with neural networks. To illustrate the two methods we use *Eduard*, an application that computes shaded relief images with the described neural networks (https://eduard.earth). The first method trains a set of neural networks with elevation models with different cell sizes. After training, the cartographer selects a neural network that generates a shading with the desired level of details (Figure 1 top). The second method uses a single neural network, but the elevation model is down-sampled and filtered. Notably, the neural networks are able to retain important edges in down-sampled and filtered elevation models, while discarding irrelevant details (Figure 1 bottom).

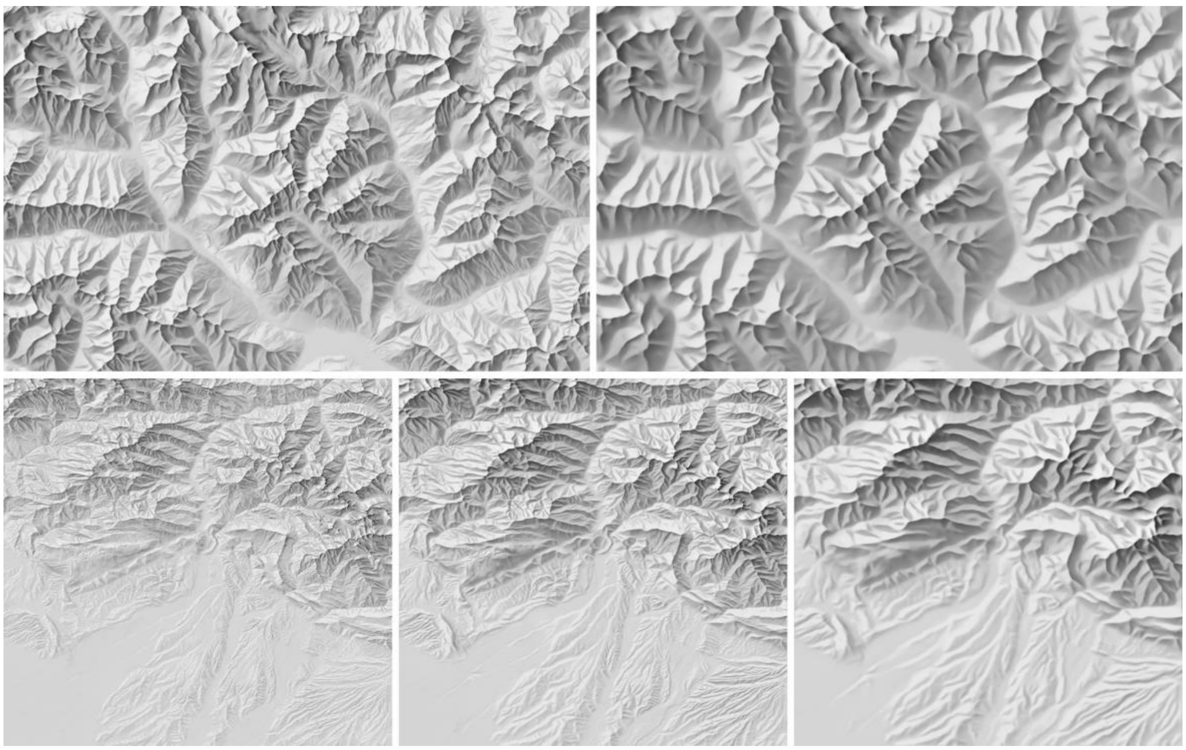

Figure 1: Adjusting the level of generalization by applying neural networks trained with reference elevation models with different cell sizes (top) and down-sampling and filtering input elevation models (bottom). Grossglockner, Austrian alps (top) and Zugdidi, Georgia (bottom). Relief shading with *Eduard*, an application for relief shading with neural networks (https://eduard.earth).

Neural Networks for Generalized Contour Lines

Our technique for generalizing contour lines uses a neural network that first transforms an excessively detailed ungeneralized elevation model to a generalized model. From the generalized elevation model, contour lines in vector format are then derived with a standard contouring algorithm. The neural networks are trained with generalized digital elevation models interpolated from (a) hand-generalized contour lines and (b) ungeneralized elevation models of the same area. We use contour lines of Russian topographic maps at 1:200,000, 1:500,000 and 1:1,000,000 scales drawn manually by the national mapping agency Rosreestr and its Soviet predecessor GUGK, as well as manually drawn contour lines from the Swiss World Atlas (2010) at a scale of 1:15 million. Elevation models are first interpolated from the contour lines, and then used to train the neural networks. Our experiments indicate that the neural networks can learn to generalize in accordance with established design principles and accentuate the representation of key landforms (Figure 2).

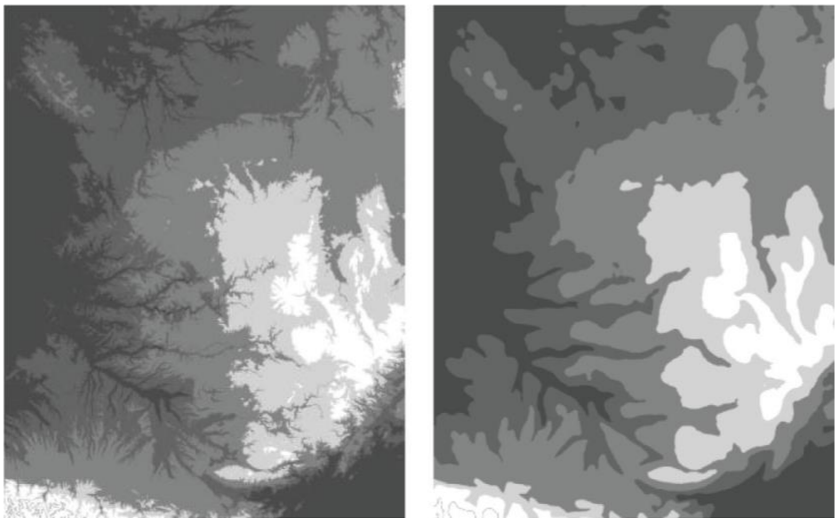

Figure 2: Contour lines derived from ungeneralized elevation model (left) and an elevation generalized with a neural network (right).

Neural Networks for Generalized Coastlines

We extract generalized coastlines from Global Surface Water, a raster dataset encoding the occurrence of surface water between 1984 and 2020 (Pekel et al., 2016). A first neural network is trained to convert the Global Surface Water raster dataset to black-and-white coastline imagery delineating continental landmasses and islands, which is then converted to vector coastlines (Figure 3).

The U-net for extracting generalized coastlines from Global Surface Water was trained with (a) recently revised generalized coastlines of the rasterized Natural Earth dataset at a scale of approximately 1:7.5 million (Kelso and Patterson, 2009) and (b) the Global Surface Water raster dataset.

Our method differs from recent machine learning techniques for the generalization of vector features, which typically necessitate an initial conversion of vector line features to raster data, then generalize the raster data with machine learning, and finally convert from raster back to vector format. Examples include work by Sester et al. (2018), Feng (2019), Touya et al. (2019a), Courtial et al. (2020), and Du et al. (2021). The required double conversion from vector to raster and raster to vector introduces a loss of information, often resulting in the appearance of fictitious or discontinuous features or other issues, as discussed by Touya et al. (2019b) and Courtial et al. (2020). Our approach avoids the initial conversion from vector to raster, as we directly extract a raster image with generalized coastlines from the Global Surface Water raster dataset.

Figure 3: Global Surface Water dataset (top) and generalized coastlines extracted with a neural network (bottom).

Conclusion

In our experiments with the three described applications, we found that high-quality generalized reference data is vital for training successful neural networks. The reference data needs to be consistently generalized and geometrically align with the ungeneralized data (such as elevation or water occurrence data). If the reference data does not meet these requirements–for example, when a reference shaded relief shows non-existing or misplaced terrain features–the network “gets confused” during training as it receives contradicting information and produces inconsistent results when asked to generalize a dataset after training. In our case, we spent considerable time and efforts preparing high-quality reference data. For relief shading, we use manual shaded relief images of the Swiss topographic map series at various scales, for creating generalized contour lines, we use manually generalized Russian and Swiss contour lines, and for creating generalized coastlines, we use manually generalized and recently revised coastlines of the Natural Earth dataset.

Figure 1 demonstrates two complementary methods for generalizing shaded relief with neural networks. Networks can either be trained with reference data at different generalization levels, or the resolution of input data can be adjusted when trained networks are applied to create generalized representations. It is interesting to observe that these two complementary methods apply to all three applications presented. That is, the amount of generalization in shaded relief, contour lines and coastlines can be adjusted by (1) selecting a particular neural network from a set of networks trained with different reference data, or (2) resampling the resolution of the input data, such as the cell size of an elevation model or surface water occurrence raster in our examples.

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