International Cartographic Association
Association Cartographique Internationale

Vectorization of watercourse detection from neural network

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Keywords: watercourses, artificial intelligence, neural network, vectorization, geometric corrections

Abstract:

There have been many studies using neural networks in recognition of watercourses by computer vision (Stanislawski et al., 2021; Lidberg et al. 2023; Koski et al. 2023). In many cases, there is also a need for a post-processing workflow to further refine the results. In our case, we have been developing a neural network workflow to detect watercourses. The detected watercourses need to be post-processed and vectorized in order to be used for topographic maps. Therefore, cartographic generalisation (e.g. Buttenfield et al., 2010; Li and Openshaw, 1992) through vectorization, line simplification and geometrical corrections of junctions is needed. The ongoing Finnish topographic mapping requires watercourses to be suitable for visualization at 1:1000 scale.

The detected outputs of the neural network models were raster images, which we vectorized and post-processed in a Python environment into a watercourse network dataset. The first phase was to vectorize the detected raster cells to polygons. The polygons were further simplified to prevent sawtooth pattern from appearing at the polygon edges during calculation of the centrelines. The library used for centreline calculation uses the medial axis algorithm and is also capable of removing groundless branches from the output. The centrelines had to be further post-processed because of distorted geometries at the watercourse junctions.

To correct the distorted geometries at junctions, the junctions were categorized into two most common types, which were four-way and three-way junctions. Three-way junctions were further categorized into T- and Y-junctions. In all cases, the line strings connected to the junctions were cut at two-meter radius from junctions to remove the distorted geometry. New junction points were calculated using old junction points or intersecting line strings. Four-way intersection had originally two junction points as can be seen from Figure 1. Calculating their centre point matches closely to the true location of the junctions. Endpoints of cut lines from T-junction are connected to the original junction point again, and the angle is calculated between two-line pairs. Then, the end points of the cut lines were taken and a new line was created between them. The new centroid of the junction is the centre of this line. New junction points of Y-junctions were calculated to find the intersecting points of the three connected lines.

As can be seen from Figure 1, the developed process vectorizes centrelines from raster data and improves the junction geometries in most cases upon visual review. However, there are still problems with the method. For example, the classification of junctions to T and Y classes can result in wrong types and incorrect corrections in borderline cases. There are also cases, where the four-way intersections are not detected and their geometries are not corrected. The generation of centrelines may still produce sawtooth patterns and the lines may not be exactly at the centre of the starting dataset. There is still work to be done to improve the results. Also, the watercourse network has gaps between watercourses. We are currently researching and developing methods to fill these gaps to form a complete watercourse network.

https://doi.org/10.5194/ica-abs-7-65-2024

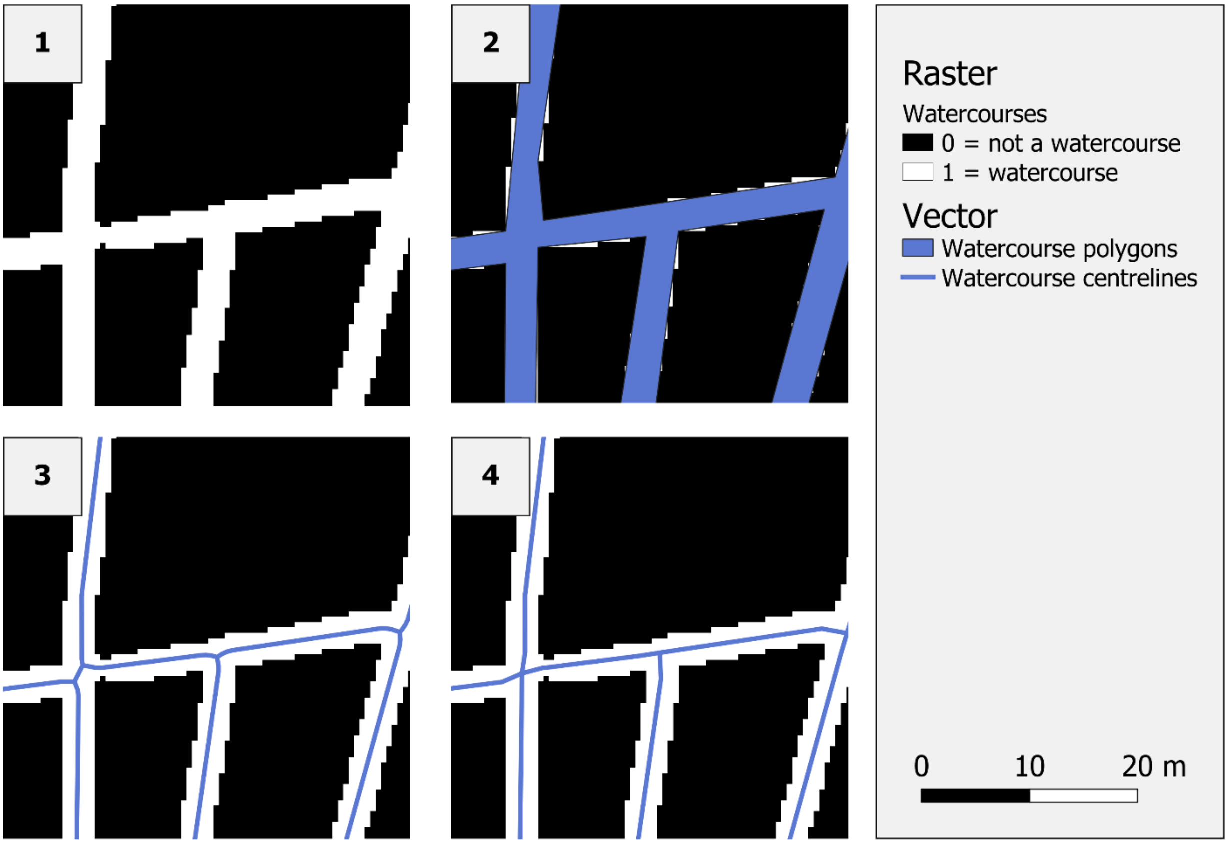

Figure 1. Vectorization of watercourse prediction raster and geometrical correction of junctions. 1) The detected raster output, 2) vectorized and simplified polygons, 3) calculated centrelines from polygons and 4) corrected junction geometry

Acknowledgements

This research has been conducted as part of the development work of the Basic Spatial Data Services of the National Land Survey of Finland and using the CSC high-performance computing by Geoportti.

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https://doi.org/10.5194/ica-abs-7-65-2024