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Experiments in the automatic segmentation of anchors using deep learning techniques

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Abstract:

The way we navigate in maps is similar to the way we navigate in real life: we look for landmarks to remember, and we create our own mind map. We define anchors in multi-scale maps as landmarks that are memorable through multiple consecutive scales. The ultimate goal of this work is to automatically detect anchors in existing maps at any zoom level. This would allow us to detect ruptures in anchor continuity and thus learn where the map could be improved to allow more seamless transitions between scales without becoming confused or lost as we zoom across the map.

Anchors are complex objects. What makes an anchor an anchor is not clear (Potié et al., 2022); anchors may be individual or groups of entities, 1 or 2 dimensional, linear, intersectional, of mixed type, and can include toponyms. Their visual interaction with other entities can alter their significance through changing scales. They are therefore difficult to model and to detect. For these reasons, our work focuses on anchor regions rather than specific anchors. We have used human-created data as the training dataset for a deep learning model that seeks to predict anchor regions in map images.

We used MapDraw (Touya et al., 2023) to build a database of anchors by asking participants to highlight anchors on the Plan IGN map, across France, at zoom levels 12, 14 and 16. A total of 114 drawings were recorded: 33 at zoom level 12, 47 at zoom level 14, and 34 at zoom level 16 (Figure 1). The participants were all experts in cartography and understood the concept of multi-scale anchors. We listed ten anchor types (Figure 2) and asked them to use different colours for the different anchors types. We stored the data as vector polygons in a PostgreSQL database.

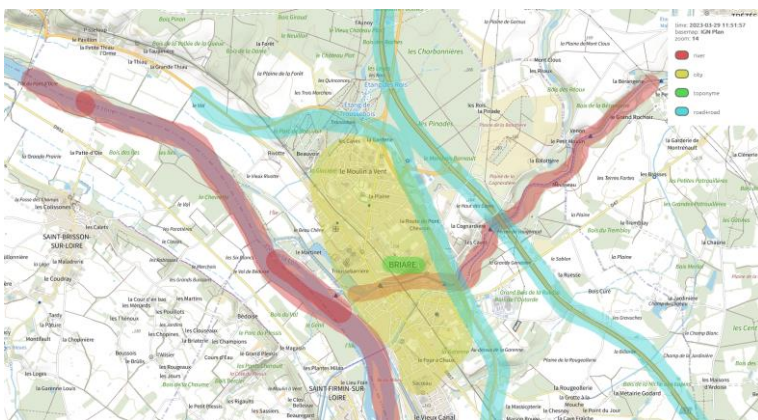


Figure 1. One drawing with Madraw (zoom level 14, test dataset).

transportation	{ road rail
overlay	{ toponym symbol
facilities	{ building city ← any size, villages included
nature	{ forest ← parks as well relief ← mountains, hills, canyons, coastal lines
water	{ river ← any water linear lake ← any water surface, glacier

Figure 2. Nomenclature of anchor types.

For our first experiment, we decided to merge all the different anchor types into a black and white mask which represents the anchor regions. The aim was to keep the model architecture as simple as possible and see if it would be able to predict anchor regions composed of a wide variety of anchors without having to indicate their nature or type. We decided to use a classical U-Net model (Ronneberger et al., 2015) with 256*256 pixel tiles as input images, with RGB channels.

Using python, we divided the extents of each drawing into several 256*256 pixel tiles. Then for each tile extent we created a pair of images: one with the Plan IGN and one with the anchor regions (Figure 3). The training dataset we used for our first experiment consisted of 2000 pairs of images, extracted from the 47 drawings at zoom level 14.

Our test dataset consisted of 7 areas in France, selected for their specific characteristics (3 urban areas, 3 rural areas and 1 coastal area). Figure 1 is one of the urban areas. Segmentation metrics as yet to be implemented, but the predictions have been evaluated visually and the results are encouraging. Figure 4 shows the 18 output tiles from the area in Figure 1 reassembled together. The whiter the pixel, the more likely it is to be part of an anchor region. This is a work in progress and we still need to determine a threshold or other process to convert the results in exploitable data.

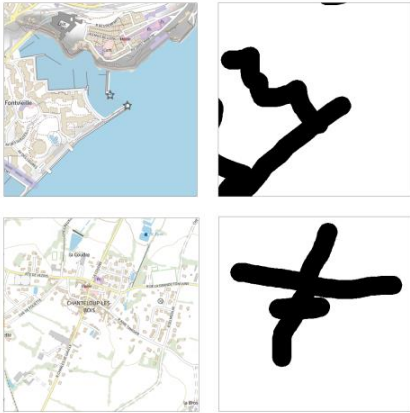


Figure 3. Two pairs image / mask

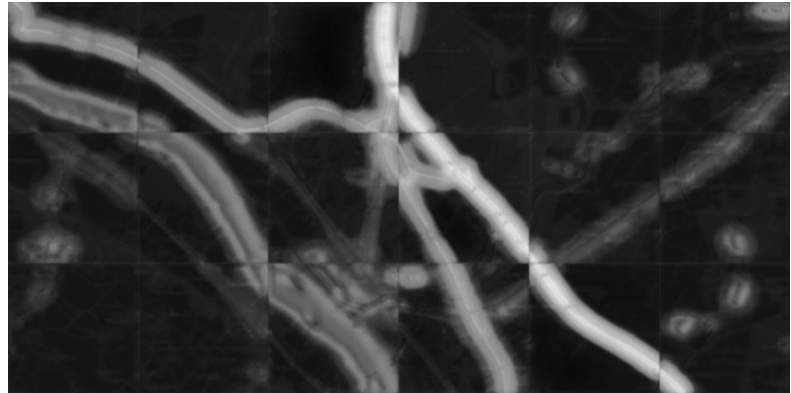


Figure 4. Model prediction for the area seen in Figure 1.

We think we can improve the model's results in the future by using larger images (512*512 pixels) to better grasp the widest anchors, or by simply increasing the dataset size. We also need to compare two approaches: is it better to train a unique model on all the scales or to train multiple models on different scales? Once this will be done, the following step will be to develop a process enabling the model to run on different zoom levels of the same area and to compare predictions in order to locate ruptures in the anchor continuity.

One limitation of our current model is that it doesn't recognise the different types of anchors, and thus can miss specific ruptures. In order to avoid that problem, future works could focus on building a model which uses multi-layered masks with one layer per anchor type instead of merging all of them in one black and white layer.

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