Detection of cultural heritage in airborne laser scanning data using Faster RCNN

Results on Norwegian data

Øivind Due TRIER, Norwegian Computing Center, Norway[1]

Keywords: grave mounds; hunting systems; charcoal kilns; automated detection; lidar

Introduction

The goal of this research is to develop automated tools for improving the cultural heritage mapping in Norway.

The existing cultural heritage mapping in Norway is incomplete. Some selected areas are mapped well, while the majority of areas only contain chance discoveries, often with bad positional accuracy.

Automated methods for detecting some types of cultural heritage objects from airborne laser scanning (ALS) data have previously been developed. These have contributed to increasing the number of areas that are mapped well. However, the methods have a number of issues that have prevented them from being used systematically on all available ALS datasets.

All of Norway will soon be covered by ALS data for the purpose of creating a new national elevation model. The Norwegian Directorate for Cultural Heritage wants to use this opportunity to obtain a more complete and accurate mapping of cultural heritage in the landscape. The focus is on Iron Age grave mounds and deer hunting systems.

The following challenges were identified: (1) develop an automated processing chain, (2) reduce processing time, (3) reduce the number of false positives and false negatives, and (4) develop detection methods that may be applied on all Norwegian landscapes.

A recent development in deep neural networks for object detection in natural images is the region-proposing convolutional neural network (R-CNN; Girshick *et al*., 2014), which may also be used for cultural heritage detection in ALS data. Verschoof-van der Vaart and Lambers (2019) use Faster R-CNN (Ren *et al*., 2017) to detect prehistoric barrows and Celtic fields in ALS data from the Netherlands.

He *et al*. (2017) extend Faster R-CNN into Mask R-CNN by providing, for each detected object, an object mask in addition to the bounding box provided by Faster R-CNN.

Data

ALS point cloud data was downloaded from http://hoydedata.no. This internet site provides free access to all ALS data in Norway.

Vector maps of known locations of grave mounds and pitfall traps were provided as ESRI shape files by the Norwegian Directorate for Cultural Heritage. Vector maps of charcoal kiln locations were provided by Oppland County Administration.

The data were split into three parts, named ‘training’, ‘validation’, and ‘test’. The neural network parameters were learned from the training data iteratively by minimising a loss function. The validation data were used to select the best set of neural network parameters. The test data were then used to estimate detection performance on data not seen during training.

Methods

Preprocessing

The ALS point cloud data were converted to a digital terrain model (DTM) with 0.25 m pixel spacing. The DTM was converted to a simplified local relief model (LRM) by subtracting a smoothed version of the DTM.

[1] Author’s address: Øivind Due Trier, Norwegian Computing Center, Gaustadalléen 23 A, P.O. Box 114 Blindern, NO-0314 Oslo, Norway; email: trier@nr.no.

The LRM enhances local elevation differences while suppressing the general landscape topography. Thus, cultural heritage objects including grave mounds, pitfall traps and charcoal kilns may be visible.

For each cultural heritage object in the vector data, a 150 m × 150 m image was extracted from the LRM. The object's position within the subimage was selected at random. This was done in order to prevent the deep neural network from always predicting the object in the image centre. All cultural heritage objects within the subimage were included in the image annotation. Thus, each image contained one or more cultural heritage objects clearly visible.

Detection

For detection, the python code library *simple faster R-CNN* was downloaded from https://github.com/chenyuntc/simple-faster-rcnn-pytorch. For each detected object the R-CNN predicts a bounding box, a class label and a score value in the range 0.0 – 1.0. A few modifications had to be done. (1) The list of class labels was changed to match the class labels used in the image annotations. (2) The downloaded code crashed if there were no detected objects within an image. Thus, if-tests had to be added.

When these changes were made, the python code predicted the location and sizes of grave mounds (Fig. 1), pitfall traps (Fig. 2) and charcoal kilns (Fig. 3) in LRM images of size 600 × 600 pixels.

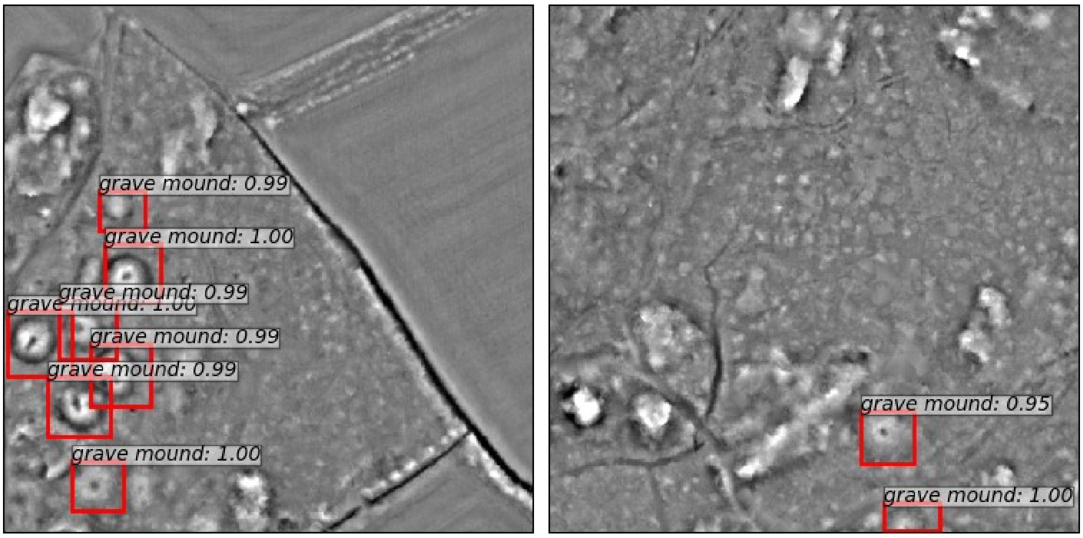

Fig. 1. Predicted grave mound locations.

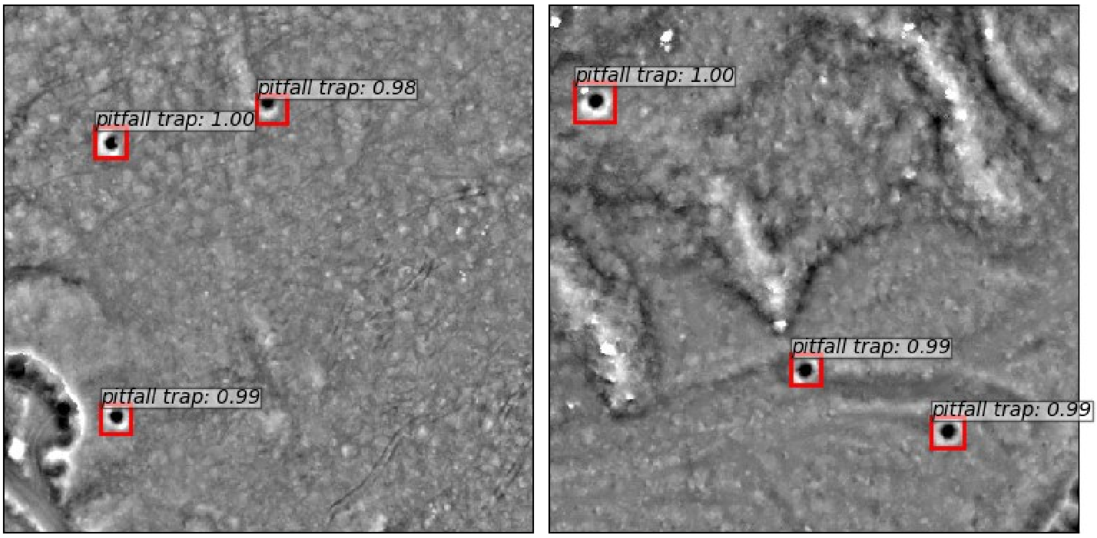

Fig. 2. Predicted pitfall trap locations.

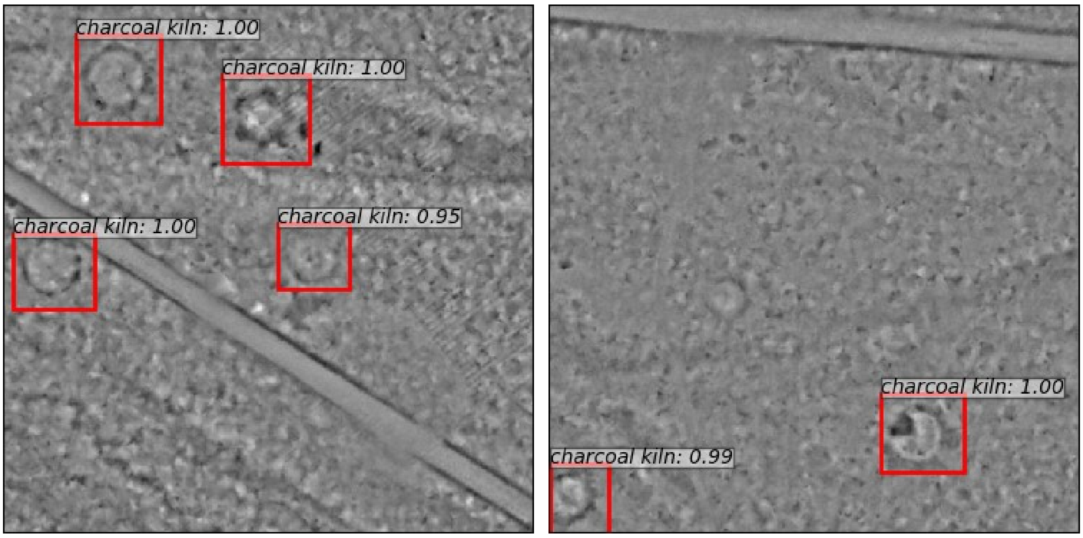

Fig. 3. Predicted charcoal kiln locations.

Processing chain

The preprocessing and detection methods were integrated into a python script that may be called from QGIS or started from the Linux command line. The input was a collection of LAS files, and the output was two ESRI shape files for each object type; centre points in one file and object outlines in another file. Each object outline was obtained by converting the predicted bounding box to a circle.

Results

By running on the test images, the overall correct classification rate was 83%, and for the specific classes, grave mound 81%, pitfall trap 78% and charcoal kiln 95%. 16% of the true cultural heritage objects were missed by the method, while 1% was detected with wrong class. 21% of the objects that the method predicted as being cultural heritage were in fact not. However, the latter figure may be an optimistic estimate of the amount of false positives that the method may provide. All the test images contained at least one cultural heritage object. In operational use, there may be large areas, within an ALS dataset, with no cultural heritage objects visible in the data. Thus, the potential for false positives is much larger. Evaluation of the detection and classification performance in such a setting will be done in the near future.

References

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