Object Detection and Classification in Digital Surface Models of the Lausitz Region in Germany

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1 Introduction

Digital surface models (DSM) derived from light detection and ranging data comprise the height profile of entire landscapes with their natural and artificial structures. Detection and classification of these structures in time series of DSM data support the administration of these regions by assessing, e.g., the growth or shrinkage of forests, geomorphic changes, for instance, bank erosion of water bodies, or urban development. Employed techniques range from image processing, machine learning [Se19] to deep learning [LDZ20].
Typically, machine learning-based approaches provide high flexibility in terms of detectable objects but they require adequate training data, whose creation can be a tedious task. Classical image-processing approaches on the other hand may detect basic shapes and contours without prior information. Pre-classification based on features like object shape, size and structure can facilitate the training data generation process.
We present work in progress towards such a multi-modal approach. Its eligibility is assessed by independently classifying objects from DSM data of the Lausitz region in Germany.

2 Method description & interim results

The analyzed data comprised a squared region of 9 km × 10 km of the Lausitz region in Germany, with a spatial resolution of 1 m in the area, totaling 90,009,000 data points, and a height resolution of 1 cm. They were acquired between the years 2005 and 2018 with at least a year between consecutive time points. For comparability, we focused on data from 2016. No other data, such as multispectral satellite data, were available.

2.1 Image processing-based analysis

The DSM data were first transformed to grayscale images reflecting the height information as pixel intensities. This representation allows two strategies for object detection: a) analyses

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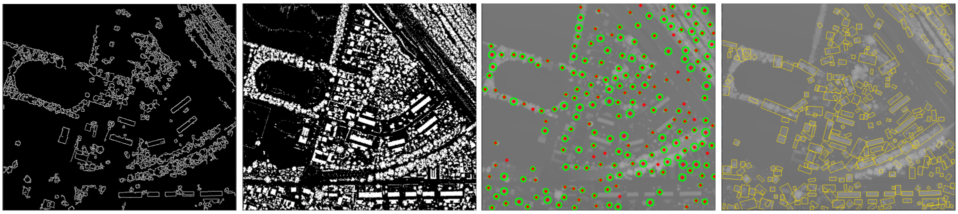
of intensity changes using gradients for the pixel-wise identification of objects and their boundaries (fig. 1a), and b) analyses of height differences for the separation of objects from the ground through thresholding (fig. 1b). Here, objects are sets of pixels with homogenous intensities, i.e., uniform height. Changes in the height properties indicate separate objects.

Since neighboring objects are not strictly isolated, special methods are required to distinguish single objects from groups of objects. The shape and size of objects can predict their class. High vegetation (trees) shall have a rounded shape, buildings a mostly rectangular one. We tested Hough circle transformation with a maximum radius of 10 m over sections of the original image to detect single big trees. While functional for single trees, this method failed to recognize groves (fig 1c). Furthermore, nearby buildings impair the detection accuracy. Determining rectangular boxes or circles in which the object optimally fits might constitute another powerful solution for detecting buildings and trees, respectively (fig. 1d).

Further analyses focused on contours of objects encompassing several advantages. Contours can reduce the data volume by only storing segments of their boundaries instead of pixel clusters. They allow the application of powerful geometric algorithms. Finally, contours may have spatial hierarchies in form of common convex hulls enclosing multiple detected objects and facilitating the detection of areas of vegetation.



(a) Gradient edge detection. (b) Thresholding. (c) Hough transformation. (d) Box fitting.

Fig. 1: Image processing based analyses in a subset of the original DSM.

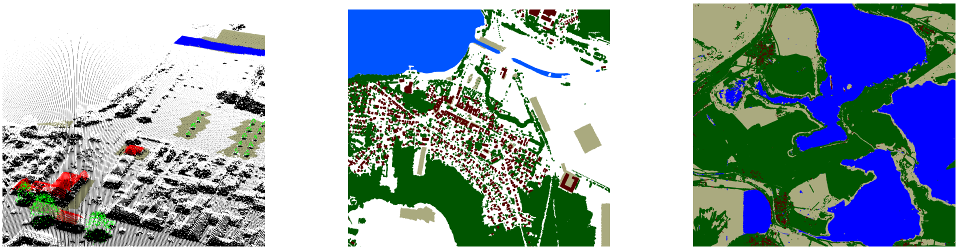
The output of the DSM analyses are closed polygons (for contours of irregular objects), rotated boxes (for rectangular objects), or circles (for round objects). Objects will be pre-classified accordingly as forests, buildings, or single trees.

2.2 Machine learning-based analysis

For the machine learning-based analyses, we employed the Computational Geometry Algorithms Library (CGAL) v.5.1.1. The DSM data were analyzed as point clouds using the CGAL Classification concept implementing a supervised random forest classifier [Wa14]. We distinguished between the classes ground, vegetation, buildings, and water.

Training data were created semi-automatically from few fully manually labeled objects (fig. 2a). Using these initial objects, a larger sub-region of 500×500 m was automatically classified (fig. 2b), manually corrected, and used as training data for the entire region.

The classification focused on the following features that were computed prior to classification: for each point the distance to 1) a locally estimated plane, 2) the global estimation of the ground, 3) the highest point of its surroundings, and 4) the lowest point of its surroundings was determined. For local point neighborhoods (n = 12), 5) the eigenvalues of their covariance matrices, 6) the dispersion along the z-axis, 7) the range between the highest and lowest points, and 8) the difference between the local normal vector and the vertical vector were computed. The classification was hierarchically executed in 6 levels of detail and regularized to ensure homogeneous results. While working reasonably in smaller sub-regions with accuracies > 0.9, the accuracy of the classification of the whole dataset (fig. 2c) is limited between 0.4 and 0.5. Adjustments of the classifier parameters and further cleaning of the semi-automatically derived training data may be required.



(a) Manually labeled training data. (b) Complete training data. (c) Full classification result.

Fig. 2: Classification: red=building, green=vegetation, brown=ground, blue=water, white=not labeled

3 Outlook

Both methods, image processing- and machine learning-based, require further fine-tuning. We intend to facilitate and augment the creation of traning data by applying the described image processing workflow. Finally, the classification results from the machine learning approach will be employed to detect changes in the vegetation, building development, or water banks across multiple years.

Bibliography

[LDZ20] Liu, Bo; Du, Shihong; Zhang, Xiuyuan: Land Cover Classification Using Convolutional Neural Network with Remote Sensing Data and Digital Surface Model. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 3:39–43, 2020.

[Se19] Sevgen, Sibel Canaz: Airborne lidar data classification in complex urban area using random forest: a case study of Bergama, Turkey. International Journal of Engineering and Geosciences, 4(1):45–51, 2019.

[Wa14] Walk, Stefan: , ETH Zurich Random Forest Template Library. ETH Zurich, Department of Civil, Environmental and Geomatic Engineering, Institute of Geodesy and Photogrammetry, 2014.