Development of large scale 3D point cloud processing modules – minimizing the number of input parameters through statistical modeling and optimization

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Abstract: The main objective of this thesis was to develop a pipeline of 3D point cloud processing modules, facilitating the extraction of training data for supervised classification tasks. The modular design enables the application of each module as standalone tools for filtering, segmentation or information retrieval.
Core component of most modules is a ground filtering algorithm, devised as a combination and further development of two well-established methods by WANG et al. (2015) and ZENG et al. (2016). The ground filter is thoroughly tested for robustness through a range of freely available benchmark datasets. Its performance is further compared to results produced by multiple methods tested on equal data.
In order to reduce the number of necessary parameters, an optimized general parameter set is produced through a regression model. The resulting default parameters prove to be applicable to a wide range of scenarios.
For further ground filtering improvements, a method for the regional segmentation of large scale outdoor point clouds is proposed, resulting in spatially coherent areas of similar terrain slope. Further characteristics, such as terrain roughness, are calculated for each segment. Optimized parameters are then calculated for the respective slope and roughness classes, thus enabling the implementation of automatic parameter adjustments into the ground filter.
As a measure for the viability of the accumulative results from all proposed methods, a supervised random forest classifier is trained from data, which has been preprocessed by each module. Hereby, the facilitation of manual training data extraction, as a result of the proposed methodology pipeline, is evaluated. The performance measures of the subsequent classification, serve as evidence for the effectiveness of the training data, as a cumulative representation of all presented modules.

1 Problem Statement

The scientific literature provides a wide array of options for point cloud classification. The effectiveness of supervised classification of 3D point clouds, based on 2D and 3D shape features derived from the local point neighborhood has been demonstrated on multiple occasions (BLOMLEY et al. 2016; DEMANTKÉ et al. 2012; JUTZI 2015; WEINMANN 2016). In many cases, the main limitation is a design focused on a specific task, based either on the applied sensor type or on the captured scene. However, improvements in the area of sensors enable the capture of large areas (> 10 ha), including varying landforms and land use types with point densities > 30 points/m^2. The technology for processing such data is becoming more affordable. Therefore, the need for a more generalized approach to large scale point cloud classification arises.

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Furthermore, supervised classification requires the generation of training data. This is often a long and tedious process and great deal of time has to be spent, carefully picking the points by hand, in order to meet the following requirements for quality training:

- being as plentiful as possible while
- remaining randomly distributed,
- representing the actual class proportions and
- minimizing spatial autocorrelation.

The more extensive the data is, the more time has to be set aside for the generation of training data. Robust, unsupervised methods for segmenting the 3D points prior to training data selection facilitate the work flow. Here, methods for filtering the ground points (GP) are of utmost significance and numerous studies, especially progressive TIN densification (PTD) approaches, have produced valuable results and are under constant development (NIE et al. 2017; ZENG et al. 2016).

Further publications also address the problem of retrieving information from the remaining non-ground points (NGP), in order to extract either building or vegetation point clusters (TÓVÁRI 2006; WANG & TSENG 2014). However, RAMIYA et al. (2016) point out, that the issue of automatically separating tree from building clusters, when both cluster classes are to be returned, is scarcely covered in literature. Again, the methods found in literature are often bound to specific landforms or land uses and the results also rely on the fine tuning of multiple parameters.

Hence, any supervised classification task of large scale 3D points would benefit from a robust ground filtering algorithm, unaffected by varying data attributes like terrain slope or roughness. Furthermore, additional subsequent methods for processing the remaining NGP are also beneficial. Most unsupervised methods studied in the course of this thesis, rely on the fine tuning of multiple input parameters.

The presented study aims at solving all afore mentioned problems.

2 Methods

Figure 1 displays the proposed methodology pipeline passing through every developed module, with the aim of facilitating training data extraction and generating additional features for the improvement of supervised 3D point cloud classification.

2.1 Low outlier filter

Outlying points below the true ground are removed, as they could otherwise cause problems with the ground filter. This is achieved through iteratively executing a simplified version of the ground filter, outlined in section 2.5.1, while inverting the z-axis after every step.

2.2 Statistical model and parameter optimization

A regression model, as part of the ground filter, is trained in advance with a wide range of training data. Based on the features resulting from the regional segmentation module, parameters for the ground filter and the cluster segmentation within the semi-supervised classification / segmentation module are optimized.

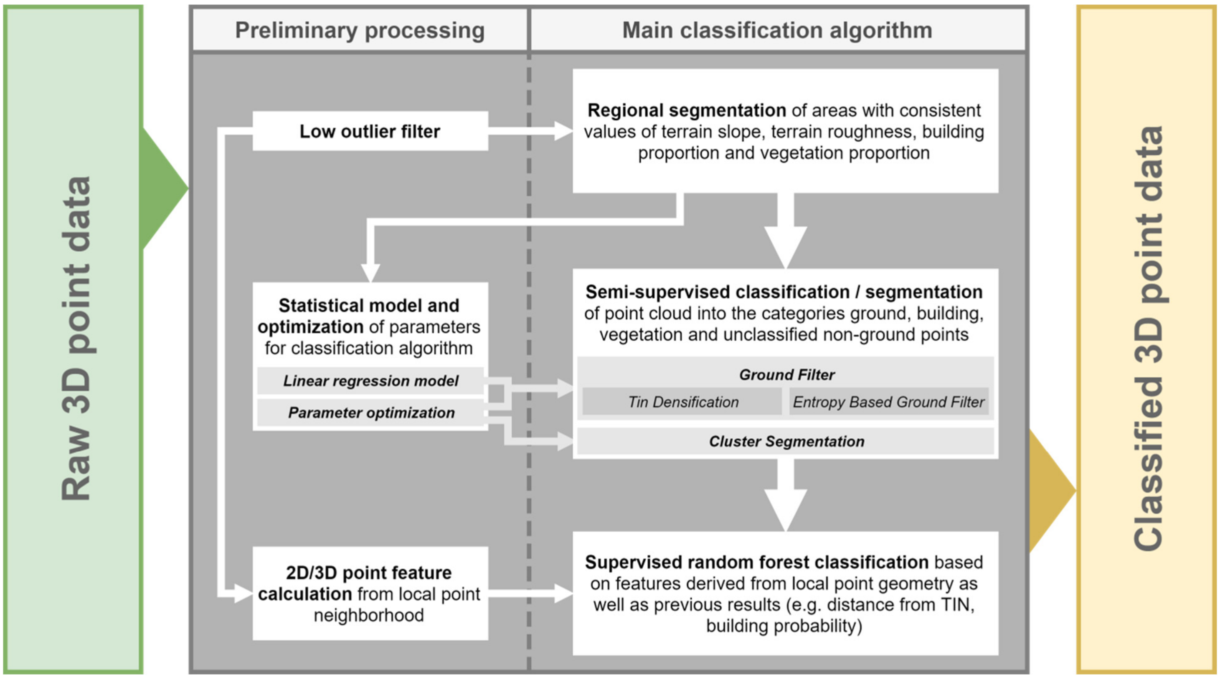

Fig. 1: Overview of the classification pipeline with the various processing modules grouped into preliminary processing modules and the main classification algorithm. Raw 3D point data is the input and semantically classified 3D point data the output of the pipeline.

2.3 2D/3D point feature calculation

Based on circular (2D), spherical (3D) and gridded (3D) local point neighborhood of each point, 2D and 3D shape features are derived, mainly calculated from respective eigenvalues. While the resulting features mainly serve as input for the supervised random forest classification module, features like linearity, planarity or scattering are independently informative, justifying a separate module for the feature calculation.

2.4 Regional segmentation

The filtered point cloud is segmented into regions of coherent terrain slope for which additional features, like terrain roughness or the proportion of probable vegetation and artificial structures, are calculated.

2.5 Semi-supervised classification / segmentation

With a preceding regional segmentation, each previously segmented region is processed individually. With the parameters adjusted through the regression models, in a first step, the GP are separated from the NGP. In a second step, the NGP are spatially clustered and every cluster is searched for planarly organized points as an indicator of unnatural objects. The resulting categories are: ground, probable building cluster, probable vegetation cluster, and unclassified NGP.

2.5.1 Ground filter

The ground filter consists of two main algorithms. In the TIN densification, the lowest point in each grid cell serves as the initial TIN vertices. Based on the triangle characteristics, the regression model predicts the tolerated height difference for each triangle. Points with a vertical TIN distance below the calculated threshold are potential GP in the next densification iteration. Once a target grid size is reached, the remaining GP are extracted through an entropy based ground filter. The switch to an entropy based ground filter substantially increases processing speeds with point clouds of high point density. Various optimized ground filter parameters are optionally set, based on preceding slope region segmentation.

2.5.2 Cluster segmentation

This module processes only NGP. Spatial clusters are grouped through Density-based spatial clustering of applications with noise (DBSCAN) and filtered by size. Planar segments are detected and serve as a measure for building / vegetation probability. Clusters with a probability between 20% and 70% are split into segment and non-segment points. Points within close proximity of the segments are added to the resulting building cluster. The remaining points result to a vegetation cluster. The planar segments are further merged into individual building clusters.

2.6 Supervised random forest classification

The results of the preceding modules simplify the training data selection for a supervised classification. The supervised classification method used here is a random forest approach based on 2D/3D shape features of the local point neighborhood. In addition to the mandatory shape features, the resulting point attributes of preprocessing steps improve the classification results.

3 Results

For all 10 terrestrial laser scanning (TLS) reference datasets from BRODU & LAGUE (2012), none of which included outliers, the outlier filter adequately did not flag any points as outliers. While a high ratio of the present outliers is detected in many datasets, in some cases the filter misses all outliers. In others, often cases without any outliers present, the filter falsely classifies many points as outliers. In only two out of the 16 airborne laser scanning (ALS) benchmark datasets more than 30% of the outliers were missed. In six cases all outliers were detected. The main weaknesses of the outlier filter are false positives in areas with jump edges or regions with few true ground points. Applying the outlier filter to aerial based photogrammetric point cloud data demonstrates an advantage of this method over methods such as statistical outlier removal. Aside from isolated low outliers, also outlier clusters are correctly flagged, resulting in unprecedented ground filtering results.

Based on visual examination, the results from the regional segmentation module capture the varying terrain characteristics very well. Problems only arise in cases where erroneous ground filtering results, based on the default parameter set, precede. Manual adjustment of said parameters significantly improves the regional segmentation outcome.

The main reference for the ground filtering results is the benchmark data from SITHOLE & VOSSELMAN (2003), on which a wide range of methods have been tested. With a mean total error of 4.90 and a mean kappa-coefficient of 84.38 the proposed ground filtering algorithm is only outperformed by two out of the 14 compared methods, proposed by CHEN et al. (2013, 2016), displaying total errors of 4.11 and 3.03 and kappa-coefficients of 86.27 and 89.44. The proposed method without preceding regional segmentation is thus already able to produce results similar to the leading methods, and additional regional segmentation cannot improve the results for the

benchmark datasets. Tested on data including regions of very steep terrain, the ground filter performance is much better, if the steep regions are segmented and processed individually with automatically adjusted parameters. None of the compared methods featured data of similarly steep terrain. It is also vital to notice, that the benchmark data was recorded in 2003 and does not represent the point density attainable with modern sensors. It is conceivable that, given new benchmark data, the proposed method displays a significant advantage in processing speed.
A visual representation of the results of a supervised classification is displayed in figure 2. Aided by all previously generated results, manual training data selection is accomplished within under an hour, extensively covering the entire area of the data. The mean performance measures result to an Accuracy of 0.98, a Precision of 0.75, a Recall of 0.64 and a F1 Score of 0.67. The relatively low values of Precision, Recall and F1 Score can here be attributed to the classifiers inability to capture the cable running from the top left of the image to the bottom right corner. The F1 Scores for the individual classes aside from the 'cable' class all lie above 0.84 with F1 Scores for 'ground' and 'high vegetation' at 0.98.
Aside from being valuable individual tools, the pipeline of processing modules as a whole can greatly facilitate training data selection, whenever a point cloud is to be manually subset into individual classes for supervised classification.

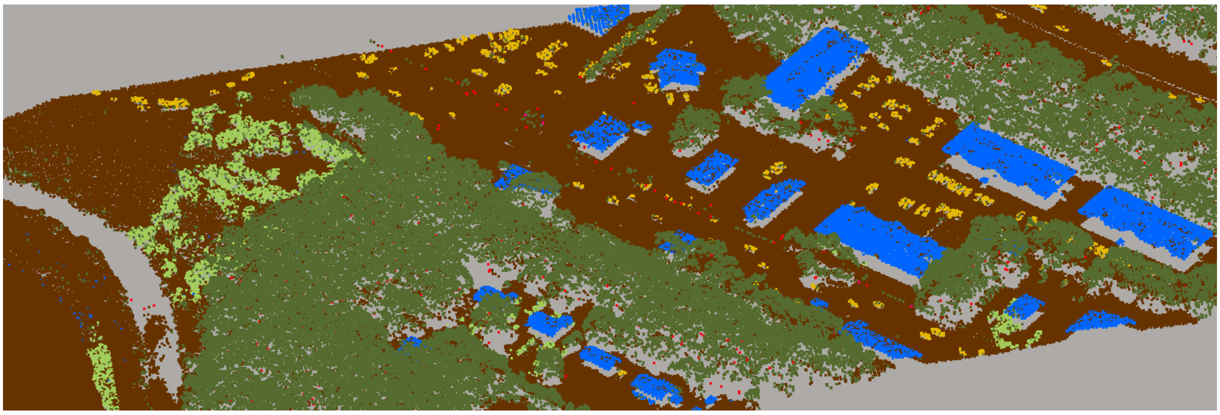

Fig. 2: Supervised classification: unclassified – red, ground – brown, low vegetation – light green, high vegetation – dark green, building – blue, vehicle – yellow. The additionally trained class cable is not visible in the depicted image.

4 Bibliography

BLOMLEY, R., JUTZI, B. & WEINMANN, M., 2016: Classification of airborne laser scanning data using geometric multi-scale features and different neighbourhood types The ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, **III**-3, 69-176.

BRODU, N. & LAGUE, D., 2012: 3d terrestrial lidar data classification of complex natural scenes using a multi-scale dimensionality criterion: Applications in geomorphology. ISPRS Journal of Photogrammetry and Remote Sensing, **68**(1), 121-134.

CHEN, C., LI, Y., LI, W. & DAI, H., 2013: A multiresolution hierarchical classification algorithm for filtering airborne lidar data. ISPRS Journal of Photogrammetry and Remote Sensing, **82**, 1-9.

CHEN, C., LI, Y., ZHAO, N., GUO, J. & LIU, G. (2016). A fast and robust interpolation filter for airborne lidar point clouds, PLoS ONE, **12**(5), 1-20.

DEMANTKÉ, J., MALLET, C., DAVID, N. & VALLET, B., 2012: Dimensionality based scale selection in 3d lidar point clouds. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, **38**(5), 97-102.

JUTZI, B., 2015: Methoden zur automatischen Szenencharakterisierung basierend auf aktiven optischen Sensoren für die Photogrammetrie und Fernerkundung. Habilitation, Karlsruher Institut für Technologie. https://hal.archives-ouvertes.fr/tel-01513489/document.

NIE, S., WANG, C., DONG, P., XI, X., LUO, S. & QIN, H., 2017: A revised progressive tin densification for filtering airborne lidar data, Measurement: Journal of the International Measurement Confederation, **104**, 70-77.

RAMIYA, A. M., NIDAMANURI, R. R. & KRISHNAN, R., 2016: Segmentation based building detection approach from lidar point cloud. The Egyptian Journal of Remote Sensing and Space Sciences, 1-7.

ROTTENSTEINER, F., SOHN, G., GERKE, M. & WEGNER, J. D., 2013: ISPRS test project on urban classification and 3d building reconstruction. ISPRS - Commission III – Photogrammetric Computer Vision and Image Analysis Working Group III / 4 - 3D Scene Analysis, 1-16.

SITHOLE, G. & VOSSELMAN, G., 2003: Report: ISPRS comparison of filters. ISPRS commission III, working group 3.

TÓVÁRI, D.; 2006: Segmentation Based Classification of Airborne Laser Scanner Data. Doctoral dissertation, PhD Thesis, Universität Karlsruhe. https://d-nb.info/1003662897/34.

WANG, M. & TSENG, Y.-H. (2014). Extraction of surface features from lidar point clouds using incremental segmentation strategy. ISPRS Journal of Photogrammetry and Remote Sensing, **19**(1), 49-62.

WANG, H., WANG, S., CHEN, Q., JIN, W. & SUN, M., 2015: An improved filter of progressive tin densification for lidar point cloud data. Wuhan University Journal of Natural Sciences, **20**(4), 362-368.

WEINMANN, M., 2016: Reconstruction and analysis of 3D scenes: From irregularly distributed 3D points to object classes. Springer International Publishing, Cham. ISBN: 978-3-319-29246-5.

ZENG, Z., WAN, J. & LIU, H., 2016: An entropy-based filtering approach for airborne laser scanning data, Infrared Physics & Technology, **75**, 87-92.