Techniques for Automated Classification and Segregation of Mobile Mapping 3D Point Clouds

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Abstract: We present an approach for the automated classification and segregation of initially unordered and unstructured large 3D point clouds from mobile mapping scans. It derives disjoint point sub-clouds belonging to general surface categories such as *ground*, *building*, and *vegetation*. It provides a semantics-based classification by identifying typical assets in road-like environments such as *vehicles* and *post-like structures*, e. g., road signs or lamps, which are relevant for many applications using mobile scans. We present an innovative processing pipeline that allows for a semantic class detection for all points of a 3D point cloud in an automated process based solely on topology information. Our approach uses adaptive segmentation techniques as well as characteristic per-point attributes of the surface and the local point neighborhood. The techniques can be efficiently implemented and can handle large city-wide scans with billions of points, while still being easily adaptable to specific application domains and needs. The techniques can be used as base functional components in applications and systems for, e. g., asset detection, road inspection, cadastre validation, and support the automation of corresponding tasks. We have evaluated our techniques in a prototypical implementation on three datasets with different characteristics and show their practicability for these representative use cases.

1 INTRODUCTION

Remote sensing technology (e. g., LiDAR) captures our physical environment at different scales with high precision using various carrier platforms (Schwarz, 2010); mobile mapping systems, for example, are commonly used in the case of urban environments and infrastructure networks. The resulting 3D point clouds have established themselves as both efficient and effective discrete digital representations of geospatial data (Vosselman et al., 2004) ("digital twins"), used in a variety of application fields, e. g., for urban planning, disaster management (Biasion et al., 2005), infrastructure monitoring and inspection (Teizer et al., 2005), facility management (Tang et al., 2010), etc. Technically, they are stored as collections of unstructured, unsorted, independent points in three-dimensional space with optional attributes attached to each point (Richter et al., 2013) (e. g., RGB colors).

Besides aerial scans, mobile mapping techniques have been established and used systems consist "mainly of a moving platform, navigation sensors, and mapping sensors" (Li, 1997); mobile carrier platforms such as cars or trains are used to capture entire infrastructure networks. Use cases include "street view" services, urban planning, pothole detection, risk analysis, e. g., for trees damaged in a storm, infrastructure monitoring, and inspection of clearance areas along roads and railroads. Mobile mapping scans can be used to, e. g., automatically construct road networks, detect and monitor assets, or to analyze road surfaces (Jaakkola et al., 2008), as well as for the reconstruction of building façades. 3D point clouds in combination with façade images can be used to extract window structures and to construct complete building models (Becker and Haala, 2007), which is important for simulations.

Applications typically require only subsets of the 3D point cloud data, e. g., points representing structures of a specific semantic type, such as roads, buildings, or certain assets. A manual classification is neither viable nor practicable for complex objects or large areas, e. g., entire cities, due to the massive amount of data. Thus, automation represents a key requirement for 3D point cloud classification. From a computational perspective, key challenges include efficient and adaptable classification and segregation algorithms for 3D point clouds taking into account object-based and semantics-based criteria (Weinmann

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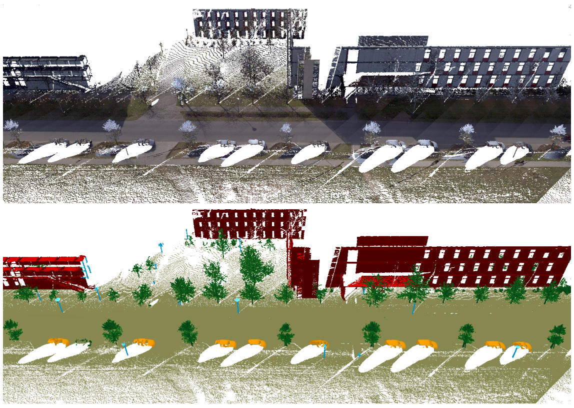


Figure 1: 3D point cloud of an urban area in RGB (top) and segregated into sub-clouds colored by semantic class (bottom). Ground: brown. Building: red. Vegetation: green. Vehicle: orange. Post-like structure: blue.

et al., 2013).

Most classification approaches for aerial data implicitly assume an aerial perspective respectively heightfield-based point distributions (Charaniya et al., 2004). Hence, they cannot be effectively applied when it comes to mobile mapping scans that show different geometric characteristics and point distributions. State-of-the-art approaches for classifying mobile mapping scans often focus on detecting a single semantic class. This paper concentrates on semantics-based classification based on the categories *ground*, *building*, *vegetation*, *vehicle* and *post-like structure* like lamps and signs, as shown in Figure 1.

In addition, we provide a scalable implementation based on out-of-core concepts to cope with large 3D point clouds (e. g., several terabytes of data) without having to reduce density or precision in preprocessing steps. All in all, this allows us automated classification and segregation via a processing pipeline that consists of multiple steps. Step by step, we compute and assign a semantic attribute to each point of the 3D point cloud given as input data.

2 RELATED WORK

Niemeyer et al. (Niemeyer et al., 2012) distinguish the five object classes "building", "low vegetation", "tree", "natural ground", and "asphalt ground" in 3D point clouds. Rutzinger et al. (Rutzinger et al., 2008) separate vegetation from non-vegetation. While most papers work on aerial 3D point clouds, classification has also been done for terrestrial scans, e. g., by Nüchter et al. (Nüchter et al., 2006), who classify points captured by a rescue robot driven indoors.

In general, separating vegetation from man-made objects is a very essential step in the classification process as described by Yao and Fan (Yao and Fan, 2013) and Grilli et al. (Grilli et al., 2017). Yao and Fan first apply a segmentation on the 3D point cloud and then classify trees within the data. Meinel and Hecht (Meinel and Hecht, 2005) describe an approach to find areas with vegetation within mobile mapping data. Rutzinger et al. (Rutzinger et al., 2011) analyze tree parameters like crown diameter and stem height for individual trees in 3D point clouds from mobile mapping scans. They create 3D models for a "representative and natural appearance of the individual trees considering the real dimensions of stems and tree crowns".

In some cases the classification is based on probabilistic Markov networks (Triebel et al., 2006); another approach analyzes the 3D point cloud's topology by specific characteristics like described by Richter et al. (Richter et al., 2013). They do not require per-point attributes or any training data and base their approach on an "iterative multi-pass processing scheme, where each pass focuses on different topological features and considers already detected object classes from previous passes".

Besides buildings, vehicles, and vegetation, cylinder-shaped structures (street lamps, signs, tree stems) are found in most mobile mapping contexts. A detection of lamps and road signs was done by Lehtomäki et al. (Lehtomäki et al., 2010), who extracted "pole-like objects" from mobile mapping data. Pu et al. (Pu et al., 2011) describe techniques to find posts and street signs and how these signs can be identified by their shapes. Fukanu and Masuda (Fukano and Masuda, 2015) convert 3D point clouds into wire frame models and use supervised machine learning methods to detect utility poles, street lamps, traffic signals, and other post-like objects. Aijazi et al. (Aijazi et al., 2013) use a voxelization approach for their segmentation.

3 CLASSIFICATION METRICS

This paper introduces an approach for the classification and segregation of large 3D point clouds from mobile mapping scans. Per-point metrics are computed in a multipass process. The classification techniques are based on the analysis of additional per-point attributes such as normal vector values and segment information. These attributes are computed for all points of the point cloud prior to the classification. Adaptive segmentation is applied to the datasets, which can then be segregated into sub-clouds based on these metrics.

3.1 Local Point Density

The local point density of a point is defined as the number of neighboring points in a certain volume around the point divided by the size of this volume. This value can be used to filter outliers and is used as a metric during the classification process.

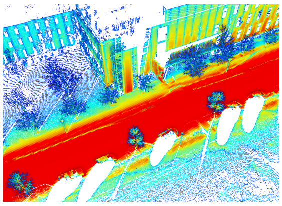
3D point clouds from mobile mapping scans usually have hugely varying point densities depending on the distance from the scanner to the target, causing the need for an adaptive analysis.

An exact computation for local point density uses a sphere with a specified radius around each point and uses the number of points within this sphere divided by its volume as the respective density value for the point in the center of the sphere. However, to be able to process large datasets in a short amount of time, an approximate computation is used instead. The scene gets separated into regular cube shaped voxels of a defined size and all points are assigned to the voxel surrounding their position. Counting the number of points in each voxel and dividing this number by the voxel's volume results in a density value for each voxel. The density for a point is defined based on the number of points in surrounding voxels. This approach is less precise, but much faster than the individual neighbor search using a sphere. As a trade-off, a side length of, e. g, 0.33 meters for the voxels has shown to deliver good results in different test data sets. Figure 2a shows a visualization of the local point density.

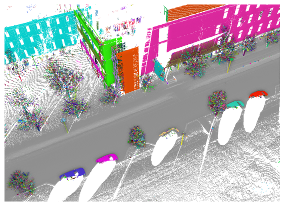
The local point density can now be used to identify areas, where point information is too sparse to make qualified statements about the semantic class of a point. Only points with a density higher than a given threshold of, e. g., 100 points per cubic meter are kept in the classification process.

3.2 Segment Size

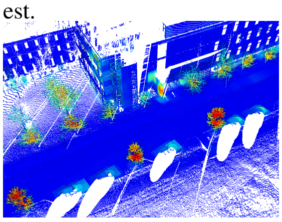
A 3D point cloud can be segmented into disjoint sub-clouds, each segment grouping together points with similar properties based on different criteria, like color, position, or normal vector orientation. In the context of classification, the segmentation creates individual segments for each object in the scanned environment. For example, all points of a vehicle will optimally be grouped into one individual segment. To achieve this segmentation, the position of points is used as well as their normal vector orientation to find connected surfaces (Rabbani et al., 2006) during a preprocessing step. Points belonging to the same surface are assigned the same segment ID which is stored as per-points attribute.



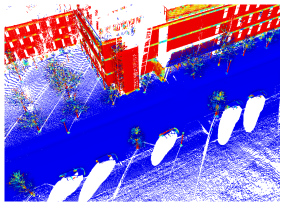
(a) Local point density. Blue points have the lowest local density, red points the highest.



(b) Segmentation. Points with the same segment ID have the same color.



(c) Segment density. Blue points have the smallest segment density, red points the highest.



(d) Verticality. Blue points have the smallest verticality, red points the highest.

Figure 2: Visualization of the different metrics.

Figure 2b shows the resulting segmentation. The number of points belonging to the same segment is used as a metric during the classification process. Building façades usually result in segments with a large number of points due to their planar structure. Vegetation on the other hand typically consists of many segments with a small number of points.

3.3 Segment Density

The segment density of a point represents the number of distinct segments that are positioned around this point. It is used to identify regions with a large number of segments, which is usually the case for vegetation areas. As described before, the segmentation aims to group points of the same object into one segment. Vegetation however is usually not segmented into clearly separated objects by the used segmentation process because of its unstructured surfaces and varying per-point normals.

The segment density can thus be used as a metric to find areas with many small segments to identify vegetation. For each part of the scene, e. g., each voxel within a voxel grid, the number of segments which have at least some of their corresponding points in this voxel or one of the surrounding voxels, is counted. Regions where this number is distinctively higher than on average are usually vegetation areas. Figure 2c shows a visualization of the segment density.

3.4 Verticality

The verticality value of a point describes the percentage of neighboring points forming a vertically oriented surface. It is used to separate upright structures like building façades from ground points and rounded objects.

The verticality is defined as the percentage of neighboring points within the same voxel, which have a horizontally oriented normal vector. All normal vectors with an angle between 80 and 100 degrees to the up vector are counted as horizontally oriented in our implementation. Figure 2d shows a visualization of the verticality metric.

Building façades have mostly horizontally facing normal vectors, so they differ from their surroundings. Ledges can have other orientations in their normal vectors, but most parts of the façades can be identified using this metric.

4 CLASSIFICATION APPROACH

The classification uses the metrics described above to determine the semantic class for each point of a 3D point cloud and to create the according segregation into sub-clouds. A preprocessing step takes place before the individual detection steps: First, all points with a local point density significantly lower than the average are filtered and marked as outliers. All outliers are excluded from the following classification process. Second, individual normal vectors are computed for each point and a segmentation based on these normal vectors is applied to the dataset.

After the preprocessing step, points for each of the semantic classes are segregated into the appropriate sub-cloud.

4.1 Ground Detection

Ground points in mobile mapping data have similar characteristics as ground points in aerial data, although point density and coverage differ. Existing algorithms are based on the assumption that ground points are usually the lowest points in a scanned area. Tests show that an established technique for ground detection in aerial data can be reused for the mobile mapping classification.

The algorithm divides the covered area into a regular two-dimensional grid. For each grid cell, the minimum z-value of all points, which fall into this cell, is stored. The result is a simplified terrain model. This approach is originally based on the paper by Meng et al. (Meng et al., 2009). It was refined by adding additional diagonal scan lines.

After the grid was initialized, scan lines are used to find all ground points of the 3D point cloud. These scan lines move axis-aligned in positive and negative direction as well as diagonally through the grid. The algorithm takes into account the slope found in the different scanning directions and how the elevation differs between points and the minimum elevation in their local neighborhood. A majority voting takes place, whether a point is a ground point from the view of each of the scan lines or not. When more scan lines find the point to be a ground point than a non-ground point, the semantic class attribute is set to *ground*.

All following classification steps analyze and operate on the remaining points which are not part of the *ground* points sub-cloud.

4.2 Building Detection

Buildings are typically the largest objects in mobile mapping scans, their façades form the most characteristic structures in the data and are processed next in the classification pipeline.

Buildings in typical urban areas mostly consist of planar vertical faces. Windows and doors are also part of the buildings as well as balconies and roof edges. As planar faces usually result in large segments, all segments with a small number of points are removed from the analysis when searching for façade points in the data. The remaining segments are filtered by their verticality. This metric was already described in Section 3.4 and is used to find vertically oriented faces.

The verticality is a value between 0 (perfectly horizontal) and 1 (perfectly vertical). Segments must at least have a verticality of 0.6 to remain candidates for the building classification. All points of the segments fulfilling these criteria are classified as *building* points. Not all points that actually belong to buildings are part of these remaining segments. Many points have been separated from the large segments and were placed into smaller adjacent segments, which should also be classified as *building* points. In a further step, points that have not been classified yet can also get the semantic class *building*, if they are located closely to already classified *building* points.

All segments of the 3D point cloud that have not already been classified are then checked one by one. Figure 3 shows, in which step the points were classified as *building* points.

Large vertical segments (blue points) were found by the process described before. Points in large seg-

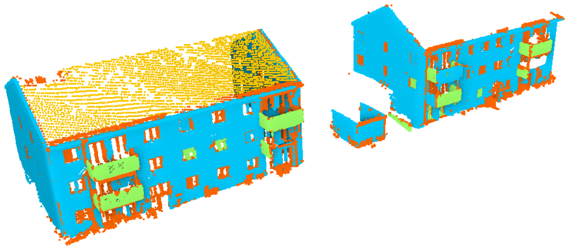


Figure 3: Buildings in a 3D point cloud. Colors represent the different steps in which the points were classified as *building* points in the following order: blue, green, orange, yellow.

ments that are within a $3\,m$ distance from the closest segment already classified as *building*, also get classified as *building* points (green points), mainly adding balconies and window frames. The same is done for all other segments regardless of their size, where at least two thirds of their points are within a $1.5\,m$ distance (orange points). This adds more window frames and other small structures. To detect roofs, large segments that are located above *building* points are also classified as *building* points (yellow points).

For performance reasons, the distances mentioned above are measured by placing all found *building* points into a voxel grid and computing the distance to the closest voxel filled with *building* points for all voxels in the grid. In this way, every voxel has an attribute describing the distance to the closest "building voxel".

4.3 Vehicle Detection

Detecting vehicles is more difficult than detecting larger structures such as buildings. Where building façades are very characteristic objects because of their large planar surfaces, vehicles do not have such a clear distinctive feature. Vehicles can have different forms and sizes, but even when concerning buses, the dimensions of vehicles are usually within certain ranges, e. g., not wider than 2.5 meters. When filtering for vehicles, the segments must have dimensions within these ranges and need to be located on the ground. The distance to the ground for a segment is determined by the average vertical height distance to *ground* points which are located beneath and close to this segment. This approach determines the ground distance also for segments that do not have any *ground* points directly beneath them, as it is often the case for parking vehicles. Segments which are not located on the ground can then be removed from the search for *vehicle* segments, all remaining segments are classified as *vehicle*, as well as small directly adjacent segments.

4.4 Post Detection

For the post detection, all remaining unclassified points are placed into a voxel grid. All voxels are examined and if they contain more than just a few single points, they are marked as being "filled", otherwise as "empty". The voxels are analyzed as if representing sliced pillars: For each x-y coordinate combination in the grid all voxels positioned upon each other are analyzed from bottom to top. As long as the voxels are filled, they are part of a potential post structure. To prevent finding thin, outstretched structures, voxels that have neighboring filled voxels together reaching more than a meter in a horizontal direction, are not processed as potential post voxels.

Once an end during the vertical processing is found, because a voxel is empty or fails the restriction described above, the height of the collected potential post voxels is calculated. If they are larger than 1.5 meters, they are marked as post voxels and all points within them are classified as *post-like structure*, as well as small directly adjacent segments.

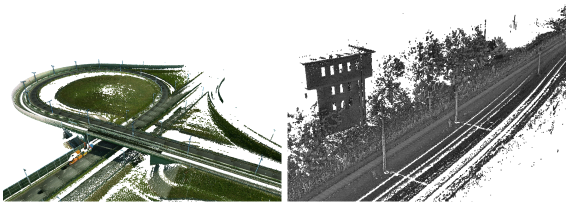
4.5 Vegetation Detection

The segment density is a good indicator for vegetation, as described in Section 3.3. Smaller structures within façades can also have a high density of very small segments, so the approach works best when being applied after the building detection.

For the given segmentation, vegetation consists of a large number of small segments. The segment density is computed for all voxels in the scene for all segments that remained unclassified after the previous steps. Points in voxels with a segment density much higher than average and with adjacent voxels with a similar high segment density are classified as *vegetation* points.

5 SYSTEM IMPLEMENTATION

The prototypic implementation, which is integrated into an existing pipeline-based 3D point cloud research framework using *C++*, *Qt* and the *Point Cloud Library* (PCL), supports customized pipelines consisting of configurable and connectable nodes via a graphical user interface. Each node is either an input node, output node, or processing node. Input and output nodes are providing I/O functionality and can read or write data files in multiple formats. Processing nodes encapsulate computations for the processing of 3D point cloud data. The discussed mobile mapping



(a) Highway dataset colored in captured RGB. (b) Railroad dataset visualized by grayscale intensity values.

Figure 4: Screenshots of the second (a) and third (b) dataset.

classification is available as a processing node and can be reused in custom pipeline configurations.

Normal vector computation is done using the PCL, approximating the surface at each point using the covariance matrix of neighboring points and the corresponding eigenvectors and eigenvalues (Hoppe et al., 1992). A segmentation based on the surface described by the computed normal vectors (Rabbani et al., 2006) completes the preprocessing.

Our processing pipeline homogenizes the data and scans are converted into one common coordinate system. Large point clouds are tiled into data chunks, which can be processed out-of-core.

A viewing application is also part of the framework (Richter et al., 2015). It can load large 3D point clouds and the visualization can be customized based on any per point attribute. The visualization allows for experimentally identifying appropriate parameters and thresholds for the classification of a specific dataset.

6 EVALUATION

For this paper, three real-world datasets with differing characteristics have been analyzed:

One dataset contains urban and suburban areas with an average point density of 3 450 points/m^2 on the road. Parked vehicles on the roads often cause "shadowed" areas in this dataset, where no points have been captured behind objects. Images from the dataset are shown in figures 1, 2, and 3.

The second dataset was captured on an on-ramp of a highway. It has an average road point density of 1 325 points/m^2. This dataset does not contain other vehicles and only low-growing vegetation.

A third dataset contains points captured by a train on a railroad track. The average point density on the track is 1 250 points/m^2. The second and third dataset are shown in Figure 4.

We have evaluated performance and accuracy of our techniques using these mobile mapping scans.

Table 1: Performance measurements. Density values are *ground* points per square meter. Time values are averaged based on three test runs with identical parameters and those for specific classification steps are normalized per 1 000 000 points.

		Urban area	Highway	Railroad
Data characteristics	Number of points	18 963 664	7 373 756	6 647 423
	Number of segments	547 324	146 543	601 152
	Volume of bounding box	7 190 580 m^3	2 461 368 m^3	625 000 m^3
	Average density	3 450 p/m^2	1 325 p/m^2	1 250 p/m^2
	Maximum density	32 124 p/m^2	2 484 p/m^2	3 494 p/m^2
Classification results	Number of points, thereof	18 963 664	7 373 756	6 647 423
	… *Ground*	56.7 %	36.3 %	67.6 %
	… *Building*	30.4 %	8.7 %	0.8 %
	… *Vehicle*	4.3 %	0.0 %	0.0 %
	… *Post*	0.3 %	0.2 %	0.4 %
	… *Vegetation*	4.2 %	2.8 %	23.6 %
	… Unclassified	4.0 %	52.0 %	7.6 %
Processing times per million points	Classification, thereof	1.04 *s*	5.55 *s*	1.71 *s*
	… Preparation and Ground	0.25 *s*	0.21 *s*	0.22 *s*
	… Buildings	0.15 *s*	0.29 *s*	0.12 *s*
	… Vehicles	0.07 *s*	0.05 *s*	0.13 *s*
	… Posts	0.23 *s*	4.69 *s*	0.19 *s*
	… Vegetation	0.33 *s*	0.29 *s*	1.05 *s*
	Processing time for complete point cloud	**19.73 s**	**40.93 s**	**11.37 s**

The approach is able to handle large 3D point clouds like city-wide scans in a both efficient and robust way, while still being easily adaptable to specific application domains and needs. Especially when taking into account how much time can be saved when exploring a 3D point cloud with semantics information in contrast to an unclassified 3D point cloud, the presented methods prove to be suitable for the classification of dense 3D point clouds from mobile mapping scans for large areas.

In the urban test region all *building* points have been correctly classified. All *ground* points in areas with a sufficient point density were found. 22 of 24 lamp posts and street signs were correctly detected and 19 of the 22 existing vehicles were found, only one group of points from a hedge was erroneously classified as *vehicle*.

In an evaluation of the railroad dataset *ground* points and *building* points were correctly identified. All 15 signal and utility poles between the rails were correctly detected.

However, some issues in the classified results exist. Especially bridges like the on-ramp of the highway pose a problem. The applied ground detection does not detect the upper ground levels, so these remain unclassified. The dataset does not contain vehicles or trees. This explains the high number of points that remain unclassified in this dataset and a large number of points is handed over from one classification step to the next, resulting in a long processing time.

The classification can efficiently be used for entire cities, Table 1 shows the processing times for the three exemplary datasets.

The complete mobile mapping dataset of the urban area consists of about 50 billion points, covers

$100\,km^2$, and uses about 920 GB of storage space. Extrapolating the measured times for the test areas shows that a classification for the complete city takes less than 15 hours for the complete dataset.

7 SUMMARY AND CONCLUSIONS

Classifying and segregating 3D point clouds from mobile mapping scans represent key functionality as it provides semantics information and allows for efficient processing of large data sets. The implementation divides ground points from building façades and vegetation; it is able to find vehicles as well as post-like structures like street lamps and sign posts. Concepts for ground detection from the field of aerial point clouds can also be used in that framework. In particular, the local point-density metrics turned out to allow us to manage the greatly varying point density typical for mobile mapping scans and can be used to filter areas unsuitable for classification if the local point-density falls under a given threshold.

Tests on different datasets show that the techniques can be used to automatically and correctly identify the semantic class points belong to, whereby we obtained the best results for ground and buildings. Detecting vehicles as well as distinguishing lamp posts from tree stems require a more detailed analysis and highly depend on the quality of the applied segmentation.

Defining the order of processing steps enables us to select the most distinctive metrics of each semantic class one at a time and, thereby, permits using the results of previous classification steps. The processing speed can be significantly accelerated using a voxel grid as spatial datastructure, i. e., the voxel-based metrics are used and their results can be applied to all points in the respective voxel if approximate values are sufficient for the current use case.

The approach also allows for a computationally fast exploration of points of a specific semantic subcloud and supports filtering options in viewing applications for detailed analysis of those objects the user is interested in. In our test scenarios, the classification could analyze about 34 million points per minute.

In summary, the object-based and semantics-based classification and segregation techniques serve as key components to process and manage large 3D point clouds from mobile mapping scans, e. g., for systems dedicated to asset detection, road inspection, cadastre validation, or municipal tasks. Semantic classification offers a number of applications, e. g., using different 3D rendering techniques for each category, and reduces the amount of data to be processed for the respective category, e. g., by storing and managing only those sub-clouds relevant to the application's purpose.

While the results of our study show that the described classification is already beneficial and robust for analyzing mobile mapping scans, the algorithms could be further improved in multiple ways. Separating buildings from ground and vegetation is the most important differentiation when segmenting 3D point clouds. However, the more detailed the classification gets, the more use cases can be covered with the data. The existing semantic classes could be used and split into multiple subclasses: Introducing a more detailed differentiation of ground points into road, curbs and sidewalks would support the detection of cars and lamp posts because assumptions about their locations could be made. Buildings could be separated into façades, doors and windows, balconies and the roof. Finding doors in buildings would enable evaluations about accessibility, especially in combination with the analysis of curb stone heights.

Mobile mapping data often contains cars and buses on the roads. A detection of cars was already implemented, but it requires each car to be segmented into only one large segment for best results. It would make sense to improve the algorithm so that it can detect adjacent segments, which together form a structure with certain characteristics.

Besides of filtering points in areas with low density, points inside of buildings could also be detected. If the location relative to already classified buildings can be identified, this enables finding points that were created because of reflective surfaces as well as points that have been scanned through a building's windows. Those points could then be removed from the classification.

3D point clouds from mobile mapping scans could be combined with data from aerial scans as well as cadastral data, which would enrich the available data pool. If data sets are combined taken at different points in time, 4D point clouds result. Extending the classification and segmentation by a temporal component would allow for new features. For example, static objects like buildings would become distinguishable from mobile objects like cars, which are not permanently fixed to a specific position. 4D point cloud enable analyses of areas that are occluded in one scan, but might be available in another scan of the same area or they could be used to analyze the same region at different times of the year, showing changes in foliation, vegetation growth, and the creation and destruction of buildings.

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