VOXEL-BASED POINT CLOUD SEGMENTATION AND BUILDING DETECTION

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ABSTRACT:

In the recent years, point cloud technologies, such as Unmanned Aerial Vehicles (UAV), Terrestrial Laser Scanners (TLS), Aerial Laser Scanners (ALS), let alone Mobile Mapping Systems (MMS), have come into the focus of attention and have been a subject of considerable public concern in mapping. Thanks to these new techniques, experts can survey large areas with sufficient and homogenous accuracy with high resolution. It comes from this that there are several areas where the point clouds can be used. One of the possible applications of point clouds is updating land registry maps. Many countries worldwide face the issue that a significant part of their large-scale land registry maps are outdated and inaccurate. One of these countries is Hungary, where more than eighty percent of digital cadastre maps were digitised using analogous maps in a scale range of 1:1000 – 1:4000. In this paper, a novel processing queue is presented to find the footprints of the building. Our solution is based on primarily well-known algorithms (RANSAC, DBSCAN) implemented in open-source Python packages. An automated flow was developed, composed of simple processing steps, to cut the point cloud into wall and roof segments and vectorise the wall points under roofs into building footprints. The algorithms and Python programs were tested in villages where detached houses are typical. Tests were made on three study areas in Hungary and we achieved well-promising results.

1. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have become popular instruments during the last two decades. UAVs have a wide range of applications from geoscience to remote sensing and engineering. Thanks to this flexibility and relatively low costs, fast and detailed mapping of the significant areas are available for anyone. The application can only be limited by imagination. (Nex et al., 2022)

One of the applications is updating land registry maps. Many countries worldwide face the issue that a significant part of their large-scale land registry maps is based on old analogue maps from the late 19th or the early 20th century. One of these countries is Hungary, where more than eighty percent of digital cadastre maps were digitised using analogous maps in a scale range of 1:1000 – 1:4000, not to mention the maps with fathom as base unit and with the scale of 1:1440 and 1:2880.

Unmanned Aerial Vehicles can provide users with a fast and affordable solution to update land registry maps. There are several examples where point clouds derived from digital images taken by UAV were used to update maps. For instance, in the Netherlands point cloud and true-orthophoto derived from images taken by UAV to identify property boundaries. (Rijsdijk et al., 2013). The result was that the necessary accuracy to do land registry mapping is achievable. The accuracy of the final product was checked by GNSS measurements, and it provide to be below 10 cm. Similar result were get in Albania (Barnes et al., 2014) and Poland (Kedzierski et al., 2016; Kurczynski et al., 2016) too.

Not only the UAV photogrammetry can provide the required accuracy. In China to increase efficiency and accuracy UAV was deployed with LiDAR sensor and was used for land registry mapping (He and Li, 2020). In the Czech Republic, an experiment was taken to compare the result of the photogrammetry and LiDAR based UAV measurements (Šafář et al., 2021).

Nowadays automation is one of the main questions. Most of the presented solutions to update land registry maps from a point cloud are based on manually processing. The question is how and how much the processing can be automated to get 2D maps from 3D point clouds?

There are several studies about the usage of UAV orthophotos for cadastral mapping. In most of these Deep Learning techniques, like Fully Convolutional Networks (FCNs) were used to classify roofs and boundaries on images in urban and semi-urban areas (Xia et al., 2019). FNCs were also used to detect changes, like new buildings, the creation of open spaces, and incremental roof upgrading (Gevaert et al., 2020). The photo-based segmentation methods are widespread, thanks to its cost efficiency it can provide a good foundation in places where cadastre maps are not available.

On the other hand, there are areas where processing of high-resolution photos is not enough. This is where different point cloud techniques come in. There are several studies where Aerial Laser Scanning-based measurements result was used to detect building roofs on large areas with combination of different segmentation and classification methods (Grilli et al., 2017), like Cloth Simulation Filtering (CSF), region growing (Shao et al., 2021). There is an approach where region growing was combined with Z coordinate histogram is analyzation to separate roof point from point clouds (Kurdi et al., 2022). There is a solution that combines region growing method over the Triangulated Irregular Network (TIN) model to refine the roof

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regions and their boundaries. From the separated roof points Level of Detail 2 (LOD2) 3D model of buildings was generated (Li et al., 2019).

Point clouds generated with UAV photogrammetry are also used to create 3D urban models. To detect building classes the combination of image and point cloud segmentation can be used. The boundaries of roofs can be determined from the semantic segmentation of the orthophoto. Using this result as a mask on the segmented point cloud 3D model of urban areas can be generated (Özdemir and Remondino, 2018).

With the help of the presented methods study data can be generated for Machine Learning and Deep Learning algorithms. There are several prepared datasets which can be used to train, and with the help of it, classify ALS (Özdemir et al., 2019) and MMS (Zou et al., 2021) point clouds.

There have been several efforts so far to detect objects in images or point clouds. Our approach concentrates on a very specific area to find building footprints on a fully automated way for cadastre mapping with enhanced accuracy (below 0.1 m). Majority of the previous works stopped to find the roofs either in orthophotos or in the point clouds.

To support automatic data processing of point clouds, a wide range of open-source software available, such as OpenDroneMap (ODM)/WebODM (OpenDronMap Development Team, 2020), CloudCompare (CloudCompare Development Team, 2022), QGIS (Cutts and Graser, 2018), not to mention many open-source libraries, like Open3D (Zhou et al., 2018), SciPy (Virtanen et al., 2020) and Scikit-learn (Pedregosa et al., 2011). Python programs were created for each processing step, sometimes alternative solutions to a specific problem, and we make it available for the community under an open-source license (GPL).

We took our measurements in villages where one or two-story detached buildings are typical. For those small settlements, small or medium Unmanned Aerial Vehicles (UAVs) can be satisfactory considering the limited flight time with a few batteries.

2. MATERIALS AND METHODS

2.1 Fieldworks

There are some essential aspects need to be taken into consideration when planning and executing flights. Making oblique images is vital to have enough points on the walls of the buildings. The best result could be achieved with double grid mission and oblique camera at 25-30 degrees. Another key point worth mentioning is to fly in seasons when the vegetation is leafless not to hide buildings.

During our tests, three campaigns were carried out with different flight parameters (Figure 1), just to name but a few, different oblique angles, single and double grid missions, with or without nadir images. To reach the required ten centimetres or even better accuracy, not more than two centimetres of Ground Sample Distance (GSD) is required.

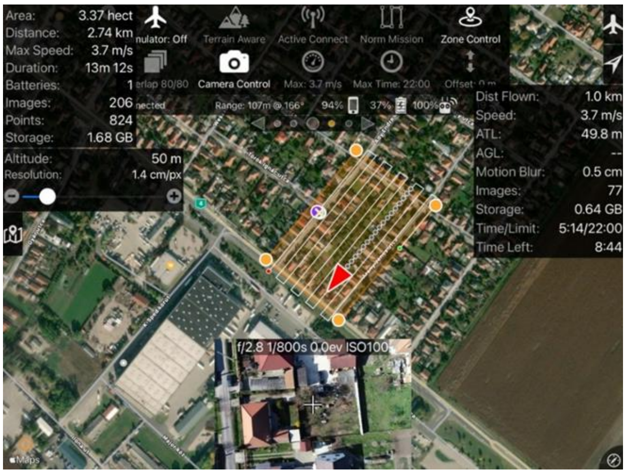

Figure 1. Grid flight mission for one of the test areas.

To improve the accuracy of the three-dimensional reconstruction from the UAV images Ground Control Points (GCPs) were used. The residuals at the GCPs are below one centimetre processing the images by OpenDroneMap.

The input data of our investigations is the point cloud of the study area. It might as well come from LiDAR observations if there are enough points on the walls of the buildings. However, in this study only photogrammetric point clouds have been tested.

2.2 Pre-processing of point clouds

Pre-classification of large-scaled point cloud is necessary to prepare raw point cloud data. After some noise removal, e.g., statistical outlier one, a subsampling could be the next step. For our specific investigation, the points on the roof and on the walls are of great importance. Usually, you get a way more points on the roofs than on the walls. A voxel-based down sampling can be used to significantly reduce the number of points on the roofs.

Separation of the roof and wall points from other points can be done using relative heights. Thus, we created a normalised point cloud by subtracting the ground height from the elevation of the points. This is done in three steps. The first one uses the Cloth Simulation Filter (CSF) algorithm (Zhang et al., 2016) to separate ground and non-ground points with high efficiency. In the second step a Digital Terrain Model (DTM) is generated from the ground points with the help of GDAL (Rouault et al., 2022). Finally, by computing vertical differences of the point cloud from the DTM a Normalised Digital Surface Model

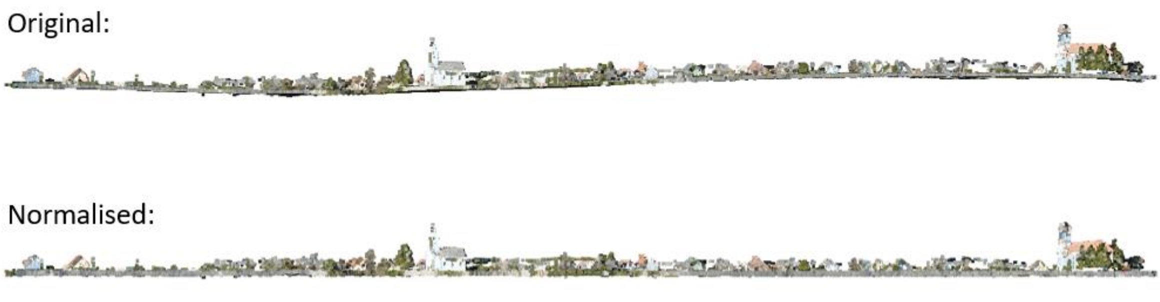

Figure 2. Vertical section of the original and normalised point cloud.

(nDSM) is generated (Figure 2). Filtering points by normalised elevations (e.g. Z > 0.3 m) in the nDSM, ground and low vegetation can also be masked. With this simplification, the size of the original point cloud can be reduced by nearly 70-80% without losing relevant data of buildings.

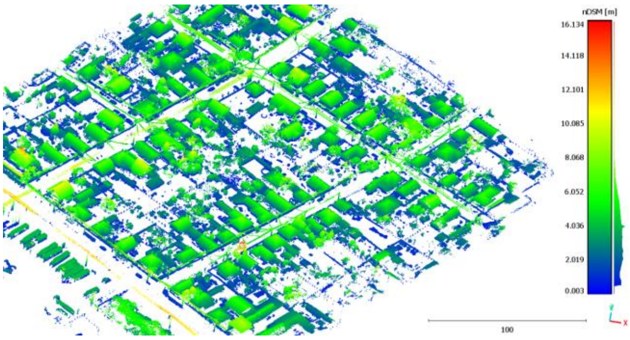

Figure 3. Normalised Surface Model, ground and low vegetation points removed.

2.3 Point cloud segmentation

In the point clouds generated from images taken by UAVs, the majority of the points are on the roofs. This can be attributed to the specialties of the data collection method. Therefore, roofs and walls should be treated separately. Thanks to the normalization, a rough filtering can be performed using the relative elevations of the non-ground points (Figure 4). It can be stated with full confidence that those points which are below a specific relative height (2.5 m, for instance) cannot be considered as roof points. On the other hand, points above the same limit can be either roof points or points on other features, as well. This way, cars, roofs, and other non-relevant features can be eliminated efficiently.

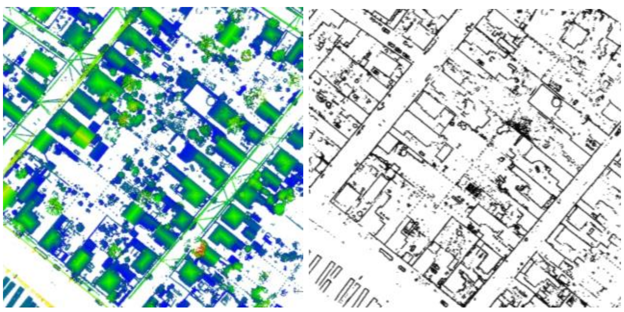

Figure 4. Normalised point cloud filtered by elevation, left above 2.5m, right below 2.5m.

Assumed that the building roofs consist of planar surfaces, the processing can be simplified to find those points that are fitting a plane in a certain threshold. Sequential RANSAC (Fisher and Bolles, 1982) offers an efficient solution to this problem.
Instead of applying RANSAC for the whole area, the point cloud was subdivided into voxels (Figure 5) to increase the efficiency of the algorithm. Voxel size can be set to between 0.5-3 meters. The sequential RANSAC is applied to these smaller blocks finding planar surfaces. Not only one but even more significant planes can be detected in one voxel. Another advantage of voxelization is that the processes can be parallelized, which makes the processing more efficient on large point clouds. Thanks to RANSAC the noise and vegetation are filtered out.

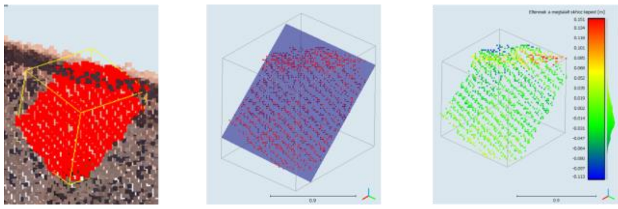

Figure 5. Planarity check in a voxel with RANSAC, left red points in the voxel, found plane in the middle, inliers, and outliers on the right.

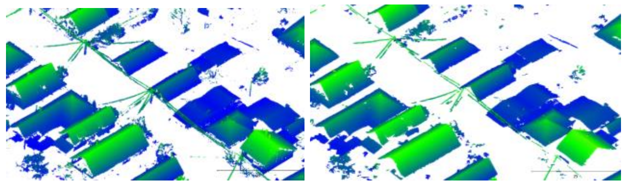

Figure 6. nDSM (left) before and after RANSAC filtering (right).

Not all planes found by sequential RANSAC are part of the roofs. The normal vectors of the planes are used to cancel non-roof parts (the angle of the normal from the horizontal direction between 0-60 degrees). The filtered voxels are combined into one point cloud yielding the roof points (Figure 6).
In the next step of the algorithm, the roofs are clustered by applying the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) (Ester et al., 1996.). DBSCAN searches for core samples with high density which are expanded by selecting the neighbouring patches. The primary advantage of DBSCAN is that it is not needed to predefine the number of clusters.
Using the lower part of the normalised point cloud (below a given relative height) the wall points can be separated. First, we tried to separate wall points like roof points applying sequential RANSAC planes, but the varying density of the point cloud made it difficult to find acceptable RANSAC parameters for all the situations. Then, the normal vectors are calculated at each point taking into account using the surrounding points in a certain radius and/or using a k-Nearest Neighbour (KNN) method. If the direction of the normal vector is close to horizontal, the point can be considered as a wall point in a vertical part of the point cloud. Segmenting the points by the estimated normal directions gives many false wall points, too, on the vegetation, on cars, etc. These false points could be dropped away by considering the roof polygons.
A further process of wall suspicious points is made using the convex hull of each clustered roof. The wall points can be filtered by bounding polygons. Before cropping wall points it is worthwhile to scale up the size of the roof polygons (Figure 7). This way point cloud of the walls can be separated by roof clusters.
At the end of the segmentation, we have several small point clouds for each building, that contains wall and roof points separately (Figure 8).

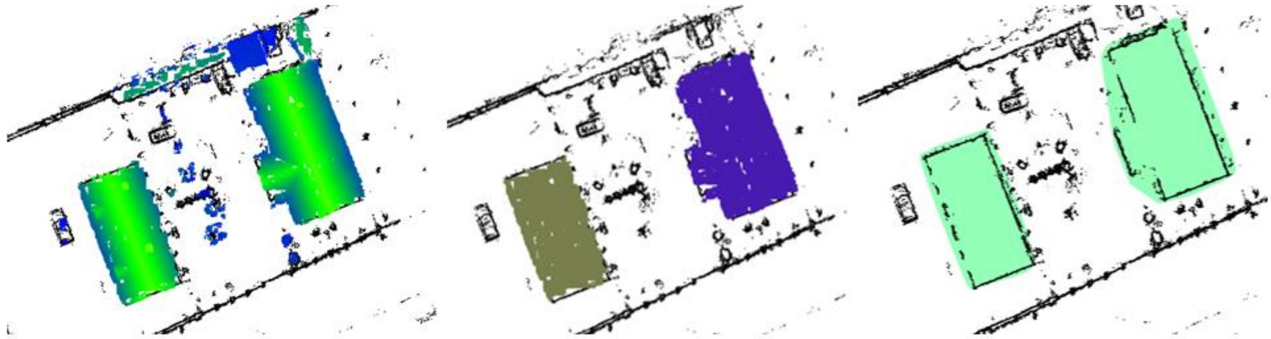

Figure 7. Roof and wall points (left), roof clusters (middle) and bounding polygon of the roof clusters (right).

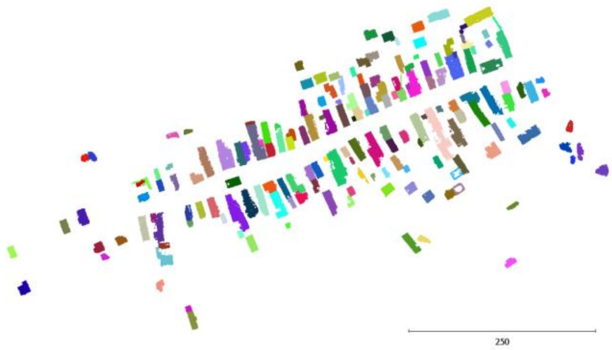

Figure 8. Clustered roof points, different clusters are marked by assorted colors.

2.4 Object detection

At this point the clustered building points could be a good starting point for the 3D reconstruction of buildings (Figure 9). Since our aim is to find 2D footprints of buildings, only the wall segment of each building is used individually in the following. As walls are supposed to be vertical, so our solution is reduced to 2D horizontal plane.

First the line equations of wall segments are searched using sequential RANSAC lines. The position of the possible corners of the building footprint are calculated by the intersection of two found lines in every combination. To find the real edges of the building footprint between the possible corner points, each pair of corner points is checked using a rectangular buffer around the edge. The buffer does not contain the close environment of the corner points. A decision is made on the density of the points (points/m^2) whether it is a real edge (Figure 10).

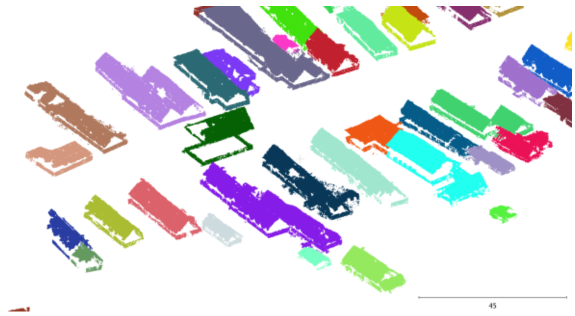

Figure 9. Clustered building points, different colours mark the corresponding wall and roof sub-point clouds.

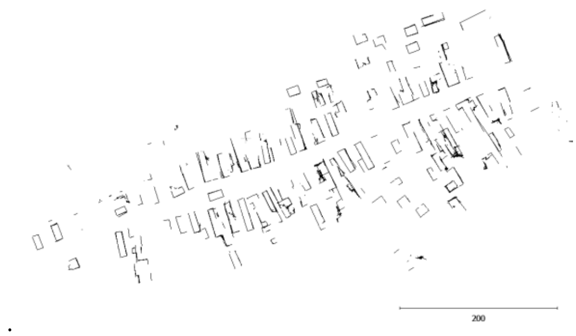

Figure 11. Detected walls at Barang test area.

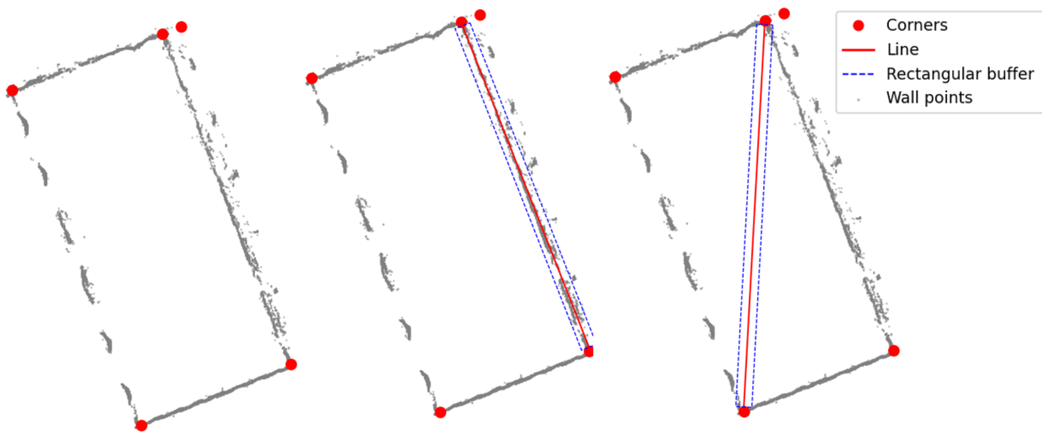

Figure 10. Intersection of the lines in every combination (red points) and the finding real edges by checking the density of the points in a buffer rectangle.

3. MEASUREMENTS AND PROCESSING

Three areas in Hungary were tested during the development of our algorithm. Photos were taken by a DJI Phantom 4 Pro UAV (Figure 12) and Ground Control Points (GCPs) were measured by RTK GNSS technique.

Figure 12. DJI Phantom 4 Pro before taking off at Üllő.

The results of our two campaigns (Barnag and Üllő) were used presented in our previous research (Hrutka et al., 2021) too. On these test areas both nadir and oblique photos were taken at 55-meter altitude AGL (Above Ground Level), having a 20 MPixel camera with 1.5 cm GSD (Ground Sample Distance). Image overlaps were set to 80% in both directions. During the grid missions the oblique angle was set to 25 degrees from the vertical.
The third test area was at Sződ which is a village north to Budapest. During the flight only oblique photos were taken in a double grid mission at 70-meter AGL with 1.9 cm GSD. The overlap was 80% and the oblique angle was set to 20 degrees.
The photogrammetric processing was carried out in ODM (OpenDroneMap), but we also used 3DSurvey. In the first test area Barnag 1400 nadir and 890 oblique photos were combined to generate point cloud. In the Üllő test area 805 images were used and in the Sződ test area 799 photos were used.

4. RESULTS AND DISCUSSION

Using the methods presented in the study, Python scripts were created and added into our public GitHub repository (https://github.com/zsiki/pc_utils). To run these scripts automatically a bash script was also created. Thus, the processing was done effectively on each test area. Table 1. shows the size of the point clouds at different processing steps.

Test areas	Number of points			
	Original	nDSM	Roof	Wall
Barnag	451 686 787	81 310 287	40 095 996	2 057 479
Üllő	115 526 471	47 113 079	25 429 088	1 825 643
Sződ	221 225 187	67 547 734	38 776 948	2 226 676

Table 1. Size of the point clouds at the different steps, nDSM without ground points.

When generating nDSM, the original point cloud's size can be reduced by nearly 70-80%. This significant reduction in size without losing relevant data can make the processing more effective with the voxelization. It can also be seen, that nearly the half of the nDSM points can be considered as roof points. The number of usable wall points is 1% of the total point clouds. During the processing voxelization plays an important role. In large-scale point clouds multi-threading made possible by voxelization and it can reduce the processing time significantly.
As a result, the processing clusters of the building were also generated. The number of these buildings was compared to the available maps. At Barnag, where updated land registry map was available the number of 163 buildings were found out of the 224 in total. At Sződ 172 building cluster were identified out of 178. At Üllő 120 building cluster were found.
Using the segmented wall points in each test area the mapping of walls was performed with the sequential RANSAC based algorithm. Since it can be stated with full confidence that the buildings are typically rectangular one, just right-angle building corners were mapped. In some more complex scenes, not every wall is found, and this situation might cause some misdraws. This error is caused by the inflexibility of the sequential RANSAC parameters. It can be fixed by applying adaptive parameters.

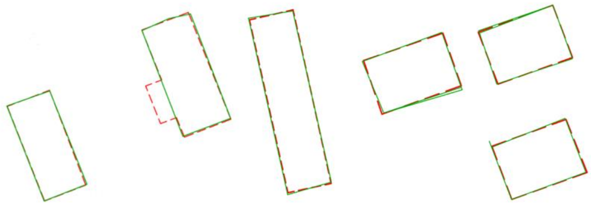

Figure 13. Some examples from the manually (red) and automatically (green) detected buildings.

Despite the abovementioned issue, quite a lot of corner points are mapped. The coordinates of these points were collected and compared to a manually created and updated land registry map. The main statistical parameters of the comparison are shown in the Table 2.

Statistical measure of the results [cm]	
Mean	22
Minimum	4
Maximum	48
Median	21
Std. dev.	11

Table 2. Statistical result of automatically founded corners compare to a manually created map of Barnag test area.

5. CONCLUSION

The main purpose of our study was to find building footprints from point clouds in order to update old and inaccurate large-scale maps with the help of open-source solutions. The

processing of point clouds was moved to mainly 3D. After noise filtering, as a pre-processing step, the original point cloud was separated into two parts: ground and non-ground points with the help of a CSF algorithm. Using these results nDSM was generated and filtered by height. During the main process we have developed solutions where parallel processing can be used to speed up the processing of huge point clouds. In addition to the combination of voxelization and sequential RANSAC, a DBSCAN algorithm was also applied to separate the roof points. To get the wall points of these roof clusters a crop was performed by the bounding polygon of roofs. Thus, the wall points were generated from the rest of the non-ground points which were filtered by height and normal direction. Finally, to find building footprint in each wall cluster sequential RANSAC lines was used.
Small Python codes were created for each step of the processing. Some cases we have alternative solutions for the same processing step, for example segmenting the wall points from the normalised point clouds. The Python codes published on GitHub are experimental, several parameters of the processing can be changed by the user from the command line or JSON configuration file to make the process more flexible and of course more difficult to use.

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