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Influence of point cloud density on the results of automated Object-Based building extraction from ALS data

Ivan Tomljenovic
Department of Geoinformatics (Z_GIS),
University of Salzburg
Schillersrasse 30, 5020, Salzburg, Austria
tomljenoviciv@stud.sbg.ac.at

Adam Rousell
Geographisches Institut,
University of Heidelberg
Berliner Strasse 48, D-69120, Heidelberg,
Germany
adam.rousell@geog.uni-heidelberg.de

Abstract

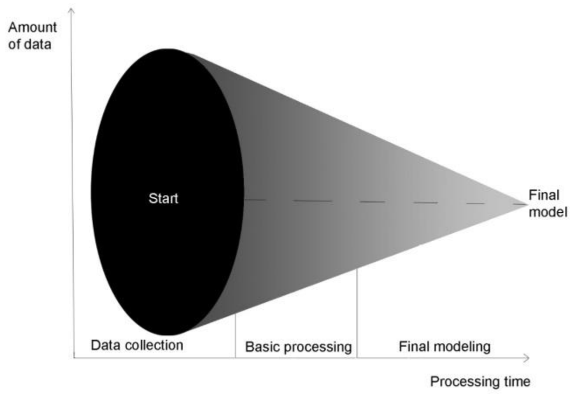
Nowadays there is a plethora of approaches dealing with object extraction from remote sensing data. Airborne Laser scanning (ALS) has become a new method for timely and accurate collection of spatial data in the form of point clouds which can vary in density from less than one point per square meter (ppsm) up to in excess of 200 ppsm. Many algorithms have been developed which provide solutions to object extraction from 3D data sources as ALS point clouds. This paper evaluates the influence of the spatial point density within the point cloud on the obtained results from a pre-developed Object-Based rule set which incorporates formalized knowledge for extraction of 2D building outlines. Analysis is performed with regards to the accuracy and completeness of the resultant extraction dataset. A pre-existing building footprint dataset representing Lake Tahoe (USA) was used for ground truthing. Point cloud datasets with varying densities (18, 16, 9, 7, 5, 2, 1 and 0.5ppsm) where used in the analysis process. Results indicate that using higher density point clouds increases the level of classification accuracy in terms of both completeness and correctness. As the density of points is lowered the accuracy of the results also decreases, although little difference is seen in the interval of 5-16ppsm.

Keywords: ALS, object-based extraction, point density, point clouds, OBIA

1 Introduction

Airborne Laser Scanning (ALS) has become a widely available tool for fast and accurate collection of data. Such a platform is capable of covering large portions of the Earth's surface within short time frames. While having a high speed of collection and thus reducing the necessary time to obtain the data the system is of great benefit, the method also generates a large amount of information. For example, the area of world's smallest country (Vatican 0.2 square miles) could generate records from 500GB up to 2-3TB depending on the chosen point cloud density. New technologies allow the production of great amounts of data in very short time intervals but they still did not provide good solutions for massive point cloud analysis, thus generating a discrepancy between time needed to collect the data and the time needed to process it (figure 1). Because of this, many scientists try to generate faster and more reliable ways of processing the data. Such processes should be as automated as possible thus reducing the influence of the human interpreter in the whole process. One of such approach used in remote sensing is Object-Based Image Analysis (OBIA). [3] recognized that using pixel-based methodologies for data extraction and classification did not provide sufficient results. [2] described in his review the benefits of the Object-Based approach and gave an overview of what has been done in the area so far. By looking at the homogenous units as conceptual wholes one can develop a system of rules which emulate the process of human thinking. By doing this (on a primitive level) it is possible to generate automated processes for data extraction. The process relies on forming the existing knowledge into a set of simplified rules under the framework of Cognition Networking Language (CNL) which is implemented within the eCognition (Trimble) software package.

Figure 1. Graphical depiction of time/data discrepancy when working with ALS data



It must be noted that it became popular to use fused data sources in order to extract information [4, 13, 14, 19, 27, 29, 36], but in our case, we use a single source in order to achieve necessary results. In the work presented here an automated process for building classification based solely on an ALS data source has been developed. For this paper it was decided to test to what extent the usage of different point cloud densities will impact the results obtained from a building extraction classification. The results of the testing will give indications as to if there really is a need to have high density point clouds and how the absence of such a source will influence the outcome. Since the algorithm is converting ALS point clouds into raster images care was also taken with regard the resolution of the data used for the analysis. It was decided to test two approaches. In the first one the resolution is varied based on the point cloud density and in the second one a consistent resolution is used whilst the input density of the point cloud is varied.

2 Previous work on object extraction from ALS data

With the development of ALS technologies and the presence of fast growing spatial data piles, research on the implementation of OBIA methodologies (segmentation and classification) touched fruitful ground. Scientists have developed many approaches which attempt to delineate and classify objects from 3D point clouds with the use of various segmentation based methodologies [1, 5, 6, 9, 10, 12, 16, 17, 18, 19, 22, 23, 24, 25, 26, 27, 28, 30, 31, 32, 33, 34, 35].

When it comes to the generation of the extraction algorithms, most researchers concentrate on domain specific solutions which range from earth surface estimation [8], geomorphic feature detection [7] and Digital Terrain Model creation [21] to modern automatic building extraction [27], automatic road extraction [11, 12], and automatic tree classification [15, 20]. These approaches are producing tangible results but they are not investigating transferability across different ALS data sources. Approaches to point cloud modelling require standardized rule sets which are universally applicable on ALS point clouds. [33] provided one of the earliest descriptions of the extraction process based only on LiDAR data. He used edge detection on an elevation model in order to define candidate objects. A predefined shape assumption (I, T or L shape) was applied in order to extract building objects. [1] used only ALS point cloud data to extract buildings. They used the first minus last pulse method with local statistical interpretation to segment the given data. [25] developed a new method for building extraction in urban areas from high-resolution ALS data. Their approach consisted of DSM minus DTM calculation, height thresholding and the usage of binary morphological operators in order to isolate building candidate regions. [17] provided segmentation and object-based classification methodology for the extraction of building class from ALS DEMs. Their classification was based on regional classification which in turn was based on cluster analysis.

All of previously mentioned approaches utilize point cloud data in order to extract information. This proves that it is possible to obtain tangible information by processing point cloud data. Even though the point clouds are mostly used in order to generate elevation models or raster representations on which the analysis methods are applied, it is still the original ALS data that is being used. Based on these observations and presented use cases an algorithm has been developed for building extraction from ALS data and testing has been performed as to show how point cloud density influences the result of the classification.

3 Methodology

In order to extract tangible objects from ALS data a specific set of rules under the framework of Cognitional Network Language which is a part of eCognition software package were developed. The approach builds on the use of a slope raster generated from the minimum height values of last returns (figure 2b). Based on the slope calculations an initial classification of the scene into hard and weak edges is performed. These classified objects are further refined with the use of pixel growing techniques and based on the analysis of the object's mean height compared to the mean height of the surrounding class it is possible to separate elevated objects from the ground surface.

Figure 2: a) generated Digital Terrain Model (DTM), b) generated digital surface model (DSM) from minimum values of last returns and c) Normalized digital surface model (nDSM) generated by subtracting DTM from DSM

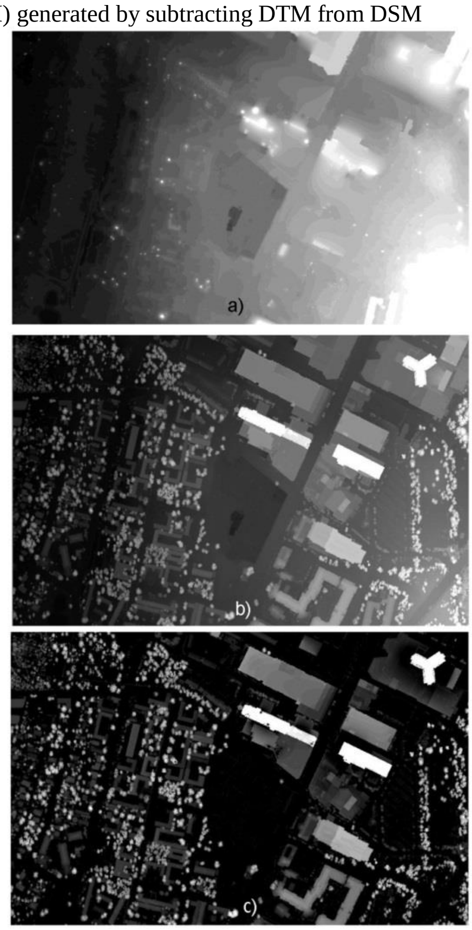
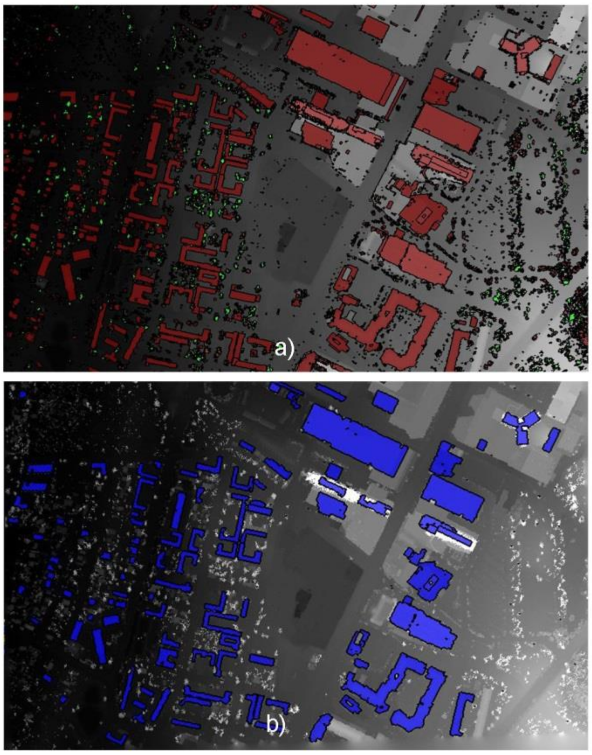


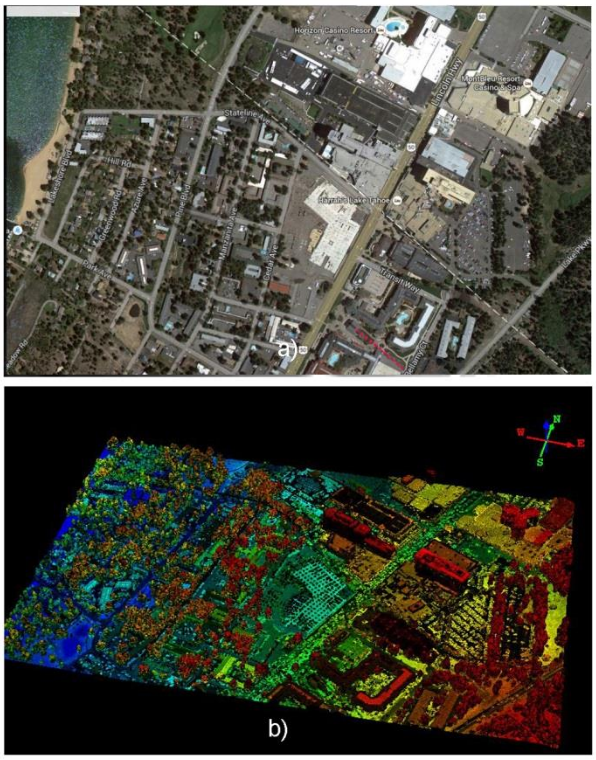
Figure 3: a) Group of objects which represent all the objects which are found above the earth's surface and b) Classified building objects



Based on a number of metrics relating to the objects (intensity, perimeter to area ratio, shape index, rectangular fit and object height) the resulting objects are classified into buildings. The remaining objects are then removed from the classification. Such extracted building objects (Figure 3b) are finally exported to the shapefile format and used for the accuracy assessment. It is important to mention that for the analysis conducted ALS data was used which represents a small area around Lake Tahoe (US) (Figure 4a and 4b). The original point cloud has the density of 18 points per square meter (ppsm).

In order to be able to perform additional testing the Quick Terrain Modeler (Applied Imagery) software was used in order to resample the initial point cloud dataset and generate point clouds with densities of 16, 9, 7, 5, 2, 1 and 0.5ppsm. Each of the newly produced point clouds was then used with the discussed classification algorithm and the resulting objects were exported into shapefile datasets. Since raster representations of surfaces (slope, DTM etc.) were used that were generated from ALS data, it was decided to make two specific use case scenarios. In the first one, the resolution of the rasters were adapted based on the point cloud density (0.25m, 0.5m, 0.75m, 1.0m, 1.5m and finally 2m) and in the second scenario rasters of constant resolution of 0.5 meters were used. All newly generated shape files that were the output of the classification process were compared to the original shape file (reference building data were provided by Spatial Informatics Group operating with funding from the Tahoe Regional Planning Agency) which contains delineated building polygons in order to calculate completes and correctness of our results. The completeness of the classification was calculated by comparing how many objects that were classified as building actually represent buildings. The goal was to compare the classification results for the object and not the absolute correctness of the polygonal shape.

Figure 4: a) Overview of the test data and b) point cloud representing test data



4 Results

Extracted polygons were exported into the shapefile (.shp) format and accuracy measures were performed using the QGIS GIS[1]. Polygon centroids were derived from the extracted polygons and an operation of "point in polygon" was performed to calculate if the extracted polygon is representing a real building polygon by comparing the centroid of the extracted polygon with the building polygons in the reference dataset. In the first case the accuracy measure is generated for the polygons extracted by using resampled point clouds and raster resolution adapted to the point density (table 1). In the second case the accuracy measure is generated for the polygons extracted by using resampled point clouds and raster resolution of 0.5m (table 2).

[1] http:// www.qgis.org/

Table 1: Accuracy results for the first case where the resolution of raster image was adapted to the point cloud density

Shape file – (resolution of raster in meters)	Density (ppsm)	Number of polygons	Polygons representing buildings	Over count	Polygon noise	Completeness (%)	Correctness (overall) (%)	Correctness (from extracted) %
Original Buildings	-	187	187	0	0	100.00%	100.00%	100.00%
Results18-0.25	18	173	154	16	3	90.91%	82.35%	98.27%
Results16-0.50	16	118	95	18	5	60.43%	50.80%	95.76%
Results09-0.50	9	118	91	27	0	63.10%	48.66%	100.00%
Results07-0.50	7	124	90	32	2	65.24%	48.13%	98.39%
Results05-0.75	5	61	38	23	0	32.62%	20.32%	100.00%
Results02-1.00	2	31	14	17	0	16.58%	7.49%	100.00%
Results01-1.50	1	13	6	6	1	6.42%	3.21%	92.31%
Results005-2.00	0.5	7	6	0	1	3.21%	3.21%	85.71%

Table 2: Accuracy results for the second case where the resolution of raster image was constant at 0.5m

Shape file	Density (ppsm)	Number of polygons	Polygons representing buildings	Over count	Polygon noise	Completeness (%)	Correctness (overall) (%)	Correctness (from extracted) %
Original Buildings	-	187	187	0	0	100.00%	100.00%	100.00%
18	18	108	103	5	0	57.75%	55.08%	100.00%
16	16	109	102	7	0	58.29%	54.55%	100.00%
9	9	117	110	7	0	62.57%	58.82%	100.00%
7	7	124	90	34	0	66.31%	48.13%	100.00%
5	5	129	117	12	0	68.98%	62.57%	100.00%
2	2	1	0	0	1	0.00%	0.00%	0.00%
1	1	1	0	0	1	0.00%	0.00%	0.00%
0.5	0.5	1	0	0	1	0.00%	0.00%	0.00%

Table 1 depicts a number of fields. The "Density" column represents the density of the point cloud, "Number of Polygons" represents the total number of polygons extracted with the classification method, "Polygons representing buildings" shows how many of extracted polygons represent a real building polygon, "Overcount" represents polygons which exist due to the over segmentation of a single structure, "Polygon noise" shows misclassified polygons, "Completeness" represents the percentage of extracted true building polygons compared to the actual number of polygons based on the ground truth data, "Correctness (Overall)" shows percentage of extracted polygons which represent single buildings compared to the base data, and "Correctness (from extracted)" represents the percentage of correctly classified extracted polygons within the obtained data. What can be observed from table 1 is that a high level of completeness and correctness (above 80%) was achieved only for the point cloud with the density of over 18ppsm. Point densities between 7-16ppsm show a middle but very stable response and everything below 5ppsm shows a very weak response (under 35%). On the other hand, if the accuracy of the classification from the extracted polygons is observed, it can be noticed that almost all the extracted polygons have above 85% correctness rate.

In the second case (table 2) the level of completeness is stable for the cases from 5-18ppsm and it evolves between the values of 48-63%. Everything below the density of 5ppsm gave a negative response of 0%. If the Correctness of the extracted polygons is observed, it can be noticed that a very high response of 100% for all the cases except the last three densities below 5ppsm is recorded.

5 Discussion & conclusions

Based on the obtained results two observational streams can be identified. In the first case, when the resolution of the data is adapted to the point cloud density, it can be observed that the high point density (18ppsm) along with very high resolution (<0.25m) will provide a high response resulting in increased accuracy. On the other hand, lower point cloud densities (7-16ppsm), along with lower resolution (0.50m), show a stable response when it comes to the accuracy, thus providing the option of using any of these since the resulting outcome will have no significant change in accuracy. In case the resolution is increased further (>0.5m) and decrease the point cloud density (<5ppsm) the results are no longer promising and the algorithm needs to be adapted to the new circumstances (parameter change is required).

In the second case, when using the same resolution of the data and only changing the point cloud densities, it is clear that the obtained response is stable for the point cloud densities of 5ppsm and above, but below 5ppsm the results are completely deteriorated and thus make a change in the algorithm necessary for such instances.

Based on the obtained results it can be determined that all the point cloud data collected with the point densities of above 5ppsm and with the resolution higher than 0.5m (if rasterisation is applied) can be used with the developed classification approach. In these cases the classification process will provide similar results thus eliminating the need from using more expensive ALS systems which provide very high densities for the collected data. The accuracy of the extraction when it comes to the internal accuracy of extracted objects is very high (>85%) which also shows that the developed algorithm proves the usefulness of OBIA methodologies when applied to 3D data sources which do not mimic human vision. Future work should focus on adapting the existing parameters (shape index, rectangular fit, perimeter to area ratio, number of returns and intensity) in order to increase the extraction accuracy of the polygons from the data so that even higher levels of completeness can be achieved through our automated approach. One of the currently considered approaches is the usage of Agent Based Modelling in order to adapt the parameters automatically based on the input data.

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