COMPARISON OF SOFTWARE FOR AIRBORNE LASER SCANNING DATA PROCESSING IN SMART CITY APPLICATIONS

V. Badenko [1,]*, D. Zotov[1], N. Muromtseva [1], Y. Volkova[1], P. Chernov [1]

[1] Peter the Great St. Petersburg Polytechnic University, Civil Engineering Institute, 195251 Polytechnicheskaya 29, St. Petersburg, Russian Federation, - (badenko_vl, zotov_dk, muromtseva_ns, volkova_yuv)@spbstu.ru, chernov_pv@edu.spbstu.ru

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ABSTRACT:

Problems of processing of point clouds of airborne laser scanning using different software for Smart City projects are considered. Results of comparison of suitable software on the base of a test point cloud are presented. For comparison we had chosen a criterion for how results of point cloud processing can be used in the smart city application. The following software were chosen for comparison: Erdas IMAGINE, ENVI Lidar, TerraSolid (without Terraslave), GlobalMapper, Autodesk InfraWorks. Comparison have been conducted in qualitative and quantitative terms. The results presented allowed us to create recommendations on the usage of specific software for airborne laser scanning data processing for Smart City projects.

1. INTRODUCTION

All type of laser scanning technologies (terrestrial, mobile, airborne) are a very popular and powerful tool for urban territory surveys to collect data during Smart City projects implementation (Balado et al., 2018; Hu et al., 2018; Li et al., 2018; Julin et al., 2018; Badenko et al., 2019; Yang and Lee, 2019). Airborne LIDAR (Light Identification Detection and Ranging) is one of the optimal modern surveying methods for urban environment (Jochem et al., 2012; Tomljenovic et al., 2015; Yan et al., 2015). In particular, this technology is effectively used to create digital terrain models (DTM) taking into account vegetation landcover and has better accuracy and quality than SRTM (Shuttle Radar Topography Mission) (Robinson et al., 2014; de Carvalho et al., 2014; Nevalainen et al., 2016; Badenko et al., 2018a; Tran et al., 2018). Also, airborne laser scanning (ALS) technology gives more information, that photogrammetry, because common this system can process more than 5-8 reflections from one laser beam, so the technology allows us to recognize DTM despite vegetation, and to define attributes of vegetation (Gorte et al., 2005; Muecke et al., 2010; Penner et al., 2015; Badenko et al., 2018b).

Analysis of the efficiency of the laser scanning data processing technologies continues to be a relevant research topic (Kaartinen et al., 2012; Xiao et al., 2016). In many cases processing of airborne laser scanning datd is much efficiency, then processing of mobile laser scanning (MLS) data (Zhou and Vosselman, 2012; Wang et al., 2018). For example, for processing of 100 km (3000 ha) MLS track survey it was needed more than 1 Tb space on a hard drive (for multi-head systems) and more than one week for processing (including registration and classification). The same ALS tile was needed only 20 Gb on a hard drive, and about few hours for creation of classification.

The objective of this paper is a comparative study of approaches and software to processing of airborne laser scanning for Smart City applications. For case study presented we have been used education versions of following software: Erdas IMAGINE, ENVI Lidar, Terrasolid (without Terraslave), GlobalMapper, Autodesk InfraWorks.

2. CASE STUDY

2.1 Initial airborne laser scanning point cloud

For Smart City application including infrastructure renovations the best data source is airborne LIDAR. Initial airborne laser scanning point cloud for comparison test experiments is shown in Figure 1.

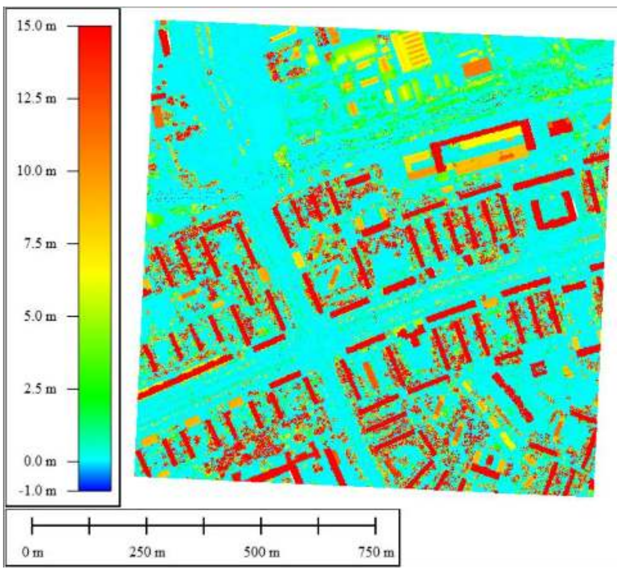

Figure 1. Initial airborne laser scanning point cloud

* Corresponding author

The point cloud had obtained by airborne laser scanning the of territory of Saint-Petersburg, Russia (one square kilometre). During scanning a complicated flight-track-adjustment software as one of the great advantage of ALS have been used (Lindenthal et al., 2011). The resolution (point spacing) of the cloud is about 0.15-0.25 meters. There are up to 6 returns from each laser beam in this cloud. The total size of the cloud is about 22 million points.

2.2 Segmentation and classification of the point cloud

Our first step was segmentation and classification of the point cloud. Classes, that are need for Smart City applications are following: Ground, Low/Medium/High Vegetation, Buildings, Model Keypoints, Wires, Vegetation Taxonomy, Roads (Zubizarreta et al., 2015; Angelidou, 2017). The features for automatic classification using software in question are shown in Table 1.

Feature type (classes)	Software which can classify the features
Ground	Erdas, ENVI, Terrasolid, GlobalMapper, Infraworks
Vegetation	Erdas, ENVI, Terrasolid, GlobalMapper
Buildings	Erdas, ENVI, Terrasolid, GlobalMapper, Infraworks
Wires	ENVI, Terrasolid, GlobalMapper
Taxonomy	ENVI, Terrasolid, GlobalMapper
Roads	ENVI, Terrasolid, Infraworks

Table 1. Abilities for classification of software in question

2.3 Comparison of software on point cloud classification task. Qualitative approach

ENVI Lidar
For this software was needed for classification about 7 minutes (the software can use all 16 CPU threads). Result of automatic classification in ENVI Lidar is shown in Figure 2.

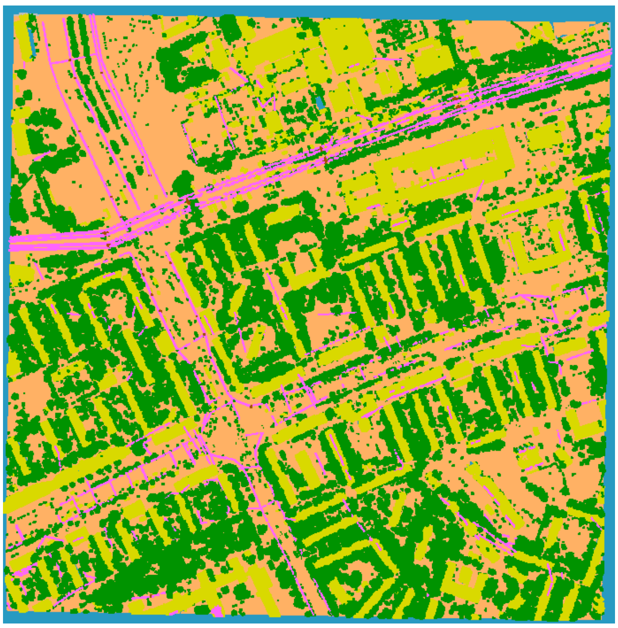

Figure 2. Result of automatic classification by ENVI Lidar

Also, there were extracted some vector features, like power wire-lines, buildings footprints with buildings height attribute. Quality of the power wire-lines is enough, but some buildings are bad-shaped. The 3D visualization is the best of all in comparison research. Vegetation taxonomy is rather good, because there is difference between hardwood and coniferous trees.
After classification ENVI Lidar provides wide opportunities for visualization. A 3d visualization after classification of the test laser scanning point cloud is shown in Figure 3. The walls of the houses are automatically depicted with a standard texture including windows only for a more realistic display. Individual trees with real crown shape are clearly visible.

Figure 3. 3D visualisation in ENVI Lidar environment

Global Mapper
For this software was needed for classification about 18 minutes. There were extracted some vector features, like power wire-lines, buildings footprints with buildings height. Quality of the power wire-lines recognition is enough, but some buildings are bad-shaped. Result of automatic classification in Global mapper is shown in Figure 4. A 3d visualization after classification of the test laser scanning point cloud 3d is good (Figure 5), but worse than ENVI Lidar visualization, because the texture for the walls and the shape of the trees are less realistic.

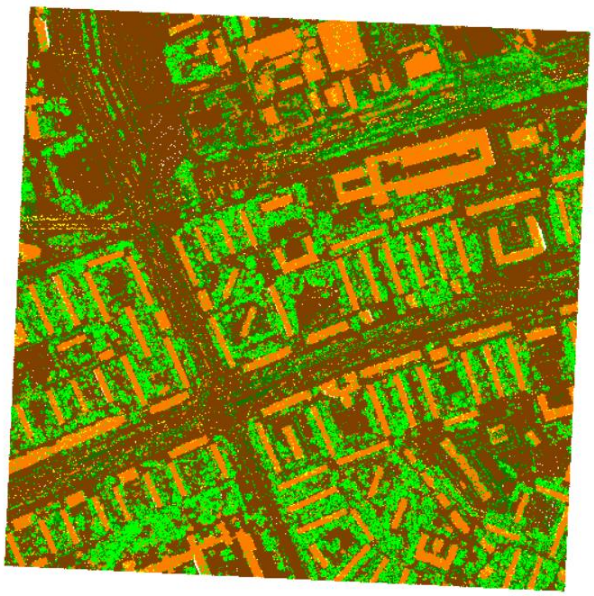

Figure 4. Automatic classification in Global mapper

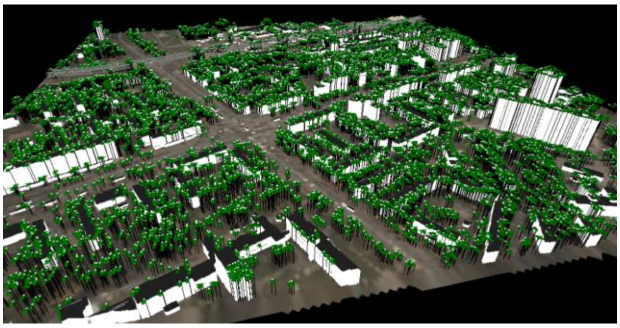

Figure 5. 3d visualization in Global mapper

Terrasolid
Software uses the MisroStation environment (Kaartinen et al., 2012). For this software was needed for classification about 20 minutes (without TerraSlave). Classification accuracy was rather good (Figure 6). There were extracted vector features, like wire-lines, buildings footprints with buildings height attribute. Also there were extracted roof slopes (Figure 7), that is very necessary to automatic building type detection. Some buildings are bad-shaped. There is no embedded 3d visualization. Roads were also extracted.

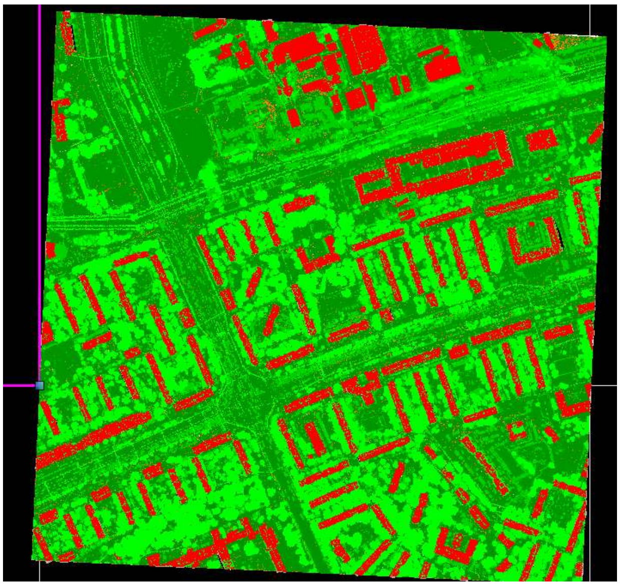

Figure 6. Automatic classification in Terrasolid.

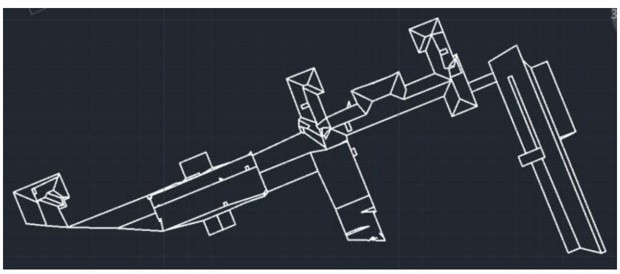

Figure 7. Roof slopes preview

Erdas IMAGINE
For this software was needed for classification about 25 minutes. The classification accuracy obtained in Erdas IMAGINE software was also quite good (Figure 8). No vector features were extracted. But there were extracted vegetation features, using NDVI (Normalized Difference Vegetation Index) (Chen et al., 2012). The calculation of the index was made possible because during the survey there was an airborne based multispectral camera.

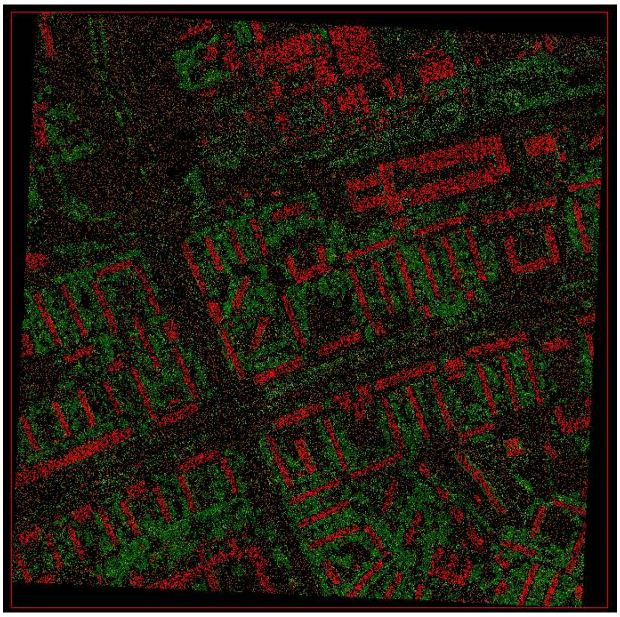

Figure 8. Automatic classification in Erdas IMAGINE.

Autodesk InfraWorks
InfraWorks can't proceed point cloud classification, and used only free data, like space photos and SRTM map. DTM is awful, no trees were extracted. But houses footprints were very good, because of smoothing (Figure 9).

Figure 9. 3d model in InfraWorks

But buildings height was awful and often did not coincide with the real (Figure 10). This software allows one to get very quickly the raw result, analyse the study area and create information only to support primary decision in Smart City projects.

Figure 10. Building height difference between lidar-based model (left) and InfraWorks (right)

2.4 Comparison of software on point cloud classification task. Quantitative approach

For quantitative comparison a following approach was used. The following classes were used for comparison (# Cl):

1. *Low points*
2. *Unclassified points*
3. *Low vegetation*
4. *High vegetation*
5. *Wires*
6. *Ground points*
7. *Buildings*

It must be pointed out that *Low points* usually includes point below surface ("aerial points") and lone points. Envi Lidar software had merged 1, 2 and 3 classes during export. Erdas Imagine also had merged 1, 2, 3 and 4 classes during export. The result of comparison of number of points in each class (#Cl) for test point cloud (Figure 1) are presented in Table 2.

# Cl	Number of points			
	Terrasolid	Global Mapper	Envi Lidar	Erdas Imagine
1	196	591	659 220	5 849 578
2	54 967	66 149	-	-
3	7 570 206	1 164 206	-	-
4	3 271 387	5 933 098	5 443 212	-
5	36 464	250 927	55 139	10 764
6	3 271 387	10 005 274	10 987 681	10 881 678
7	2 510 506	2 253 058	3 185 710	3 456 686

Table 2. Number of points in each class for different software

Some comments for Table 2 must be added. For all software sometimes the following happens. For Terrasolid: 1) cars, buildings footprints, semi-row ground points had included in class 3; 2) trees, wires, cars, house walls had included in class 4. For Global Mapper: 1) cars parts/whole, buildings footprints had included in class 3; 2) trees, wires, cars, house walls had included in class 4; 3) roof parts had included in class 5; 4) some big cars had recognized as buildings (class 7). For Envi Lidar: 1) cars, wires, house parts had included in classes 1, 2, 3; 2) trees, cars, wire poles had included in class 4; 3) roofs, walls, big cars had included in class 7. For Erdas imagine: 1) trees, cars, wires, building walls had included in class 1,2,3,4. It should also be specifically noted that the 5 class (*Wires*) of Envi Lidar is of excellent quality.

3. CONCLUSIONS

The results of software comparison on the base of test airborne laser scanning point cloud processing have presented. The comparison criterion is how results of point cloud processing can be used in the Smart City application. The following software was chosen for comparison: Erdas IMAGINE, ENVI Lidar, TerraSolid (without Terraslave), Global Mapper, Autodesk InfraWorks. We also tested the Esri City Engine. This powerful software is directly connected to the most popular GIS and therefore Esri City Engine is convenient for regional planning tasks. However, this software is not always well suited for solving engineering problems and working slower than others.

Recommendations on the usage of specific software for airborne laser scanning data processing for Smart City projects are following:

- ENVI Lidar software allows us to quickly and qualitatively classify, extract the footprints of buildings, power-lines and high vegetation. Other post-processing and uploading of data is practically not provided. This software is very useful for realistic visualization.
- The Global mapper software produces a qualitative (close to semi-automatic) classification, but because of the work in one stream, it has low performance. It is recommended to use this software if you do not have access to ENVI Lidar.
- Terrasolid software involves a large amount of preprocessing, and has a fairly high level of laser scanning data processing. The software allows us to perform fine tuning and to extract the largest amount of vector information, in particular roof slopes, which is very important for Smart City projects. An important advantage of this software is a flexible connection with CAD programs.
- Erdas IMAGINE is most suitable for environmental tasks, due to the possibility of working with multispectral images. The processing performance of point clouds is the lowest of the examined ones, but at the same time it allows solving spatial-analysis tasks. The main advantage of Erdas IMAGINE is its good and flexible connection with GIS.
- Autodesk InfraWorks and allow us to get very quickly the raw result, analyze the study area and create information support for a feasibility study.

Quantitative comparison of the quality of classification by the number of points in each class shows a significant variation. This is talking about the imperfection of the automatic classification and the relevance of this direction of further research.

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