Comparative Analysis of Automatic Methods for Road Infrastructure Elements Extraction from Point Cloud

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Key words: education, geoinformation, implementation of plans, laser scanning

SUMMARY

Spatial information is used for various purposes - creating maps of different types, digital terrain models, for traffic management and many others. As the application of spatial information expands, the requirements for accuracy, precision and level of detail increase. Laser scanning technology is one method of collecting spatial data that can follow current trends and requirements. The main output product is point cloud, i.e. set of 3D points positioned in space. As high-resolution cameras are increasingly being implemented in this laser scanning system, high-resolution photos are also being obtained. Those photos showed as very useful during visual inspection of the terrain.

Accordingly, the post-processing of data obtained with this technology implies a complete set of tasks. The goal is to group these tasks, reduce execution time and improve the final result. For example, the term inventory of road infrastructure implies structural lines: lines of edges and the middle of the road, top and bottom lines of curbs, channels, etc. In addition, the inventory includes other spatial entities, such as white lines on the road, pedestrian crossings, bicycle paths, buildings, poles, traffic signs, trees, fences, borders of different cultures.

Therefore, it is clear that the inventory of road infrastructure includes numerous elements and that manual drawing requires a lot of time. That is why an intensive work on the automation of these processes is being done. However, there are currently no completely automated solutions that extract all of mentioned elements with satisfactory quality. Certain commercial solutions offer digitization of individual elements, in ideal or closely ideal conditions. The aim of this paper is to provide a detailed insight into current achievements on the topic of automatic extraction of road infrastructure elements. The results of the research and the new proposed methodologies of automatic extraction of particular elements from point cloud will be presented. At the end of the paper, a comparison of the latest methodologies and discussions on the obtained results will be done.

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1. INTRODUCTION

Spatial information is used for different purposes – creation of different map types, digital terrain models, for navigation and many others. The choice of method for collecting these data is made on the basis of user needs, expected accuracy, level of detail and available resources. The development of new technologies is causing greater demands in many scientific disciplines. Therefore, it is necessary to possess data that is accurate, precise and efficient. Such high standards require extensive, efficient and cost-effective inspection and data collection methods, where mobile laser scanning technology finds its application. This technology requires incomparably less time in which it collects a huge amount of data (Attoh-Okine et al. 2013). The focus has changed from fieldwork to the office work. Accordingly, the trend of data post-processing improvement is on the rise, which reveals new opportunities and networking of various scientific disciplines (Layek et al. 2020, Mukupa et al. 2017, Mancini et al. 2020).

Post-processing of data obtained by MMS technology (point cloud and images) represents a complete set of tasks and procedures. The goal is to group these tasks, reduce execution time and improve the final result. One of the basic steps in the point cloud processing is its classification - points in the cloud are assigned the appropriate classes to which it belongs: soil, low, medium and high vegetation, objects, etc. Standard classes are formed automatically based on predefined rules. However, if necessary and in accordance with the requirements, other classes and algorithms for point cloud classification can be defined manually. Classification is followed by extraction of structural lines. Structural lines of road infrastructure include lines of edges and middle of the road, top and bottom lines of curbs, channels, etc. Afterwards, other spatial units are drawn, such as road markings, pedestrian crossings, bicycle paths, buildings, poles, traffic signs, trees, fences, borders of different cultures, etc.

From the above-mentioned, it is clear that the inventory of road infrastructure includes numerous elements and manual drawing that requires a lot of time. Therefore, an intensive work is done on the automation of these processes. However, there aren’t currently automated solutions that extract all of these elements with satisfactory quality. Certain commercial solutions offer digitization of individual elements, in ideal or approximately ideal conditions. The aim of this paper is to give a detailed insight into current achievements on the topic of automatic extraction of road infrastructure elements, based on data obtained by using modern geodetic technologies. The results of research and proposed methodologies of automatic road elements extraction are presented.

2. OBJECTS EXTRACTION SOLUTIONS

A lot of authors deal with automatic extraction of object boundaries on the ground or roof edge projections. This chapter gives a brief overview of some newly suggested approaches. Authors of paper (Pu et al. 2006) present automatic extraction of building features from laser scanned data. The feature recognition procedure starts with segmentation, where a point cloud is categorized into different groups so that the points belonging to the same surface or region are in the same group. The result from segmentation gives potential building features, but it is still unknown whether a segment represents a feature, or which kind of feature a segment represents. Each building feature has its own characteristics, which can be formulated as feature constraints that are understandable by machines, so automatic feature recognition becomes possible. In the final step, building features are recognized out of segments by checking each segment's properties through the feature constraints. Considering the human knowledge about building features and supposing all the building features are planar, Table 1 presents summarized set of feature constraint categories:

Table 1: Constraints for 7 features (Pu et al. 2006)

	Size	Position	Direction	Topology	Miscellaneous
Ground	Segment(s) with large area	Lowest			
Wall	Segment(s) with large area		Vertical	May intersect with the ground	
Window	Area from min < max	On the wall	Vertical		Low laser points clouds density
Roof	Segment(s) with large area	Above wall	Not vertical	Intersects with a wall	
Door	Area from min < max	On the wall	Vertical	Intersects with the ground	
Extrusion		A little bit outside the wall/roof		Intersects with a wall	
Intrusion		A little bit inside the wall/roof		Intersects with a wall	

This recognition method is implemented with C++ code, and experimented on a PC with Pentium 4 3.2G CPU, 1GB system memory and the NVidia Quadro FX540 video card. The tested point cloud contains 238034 points. Figure 1 gives some examples of detected features, while Table 2 gives the statistics of the seven features recognition.

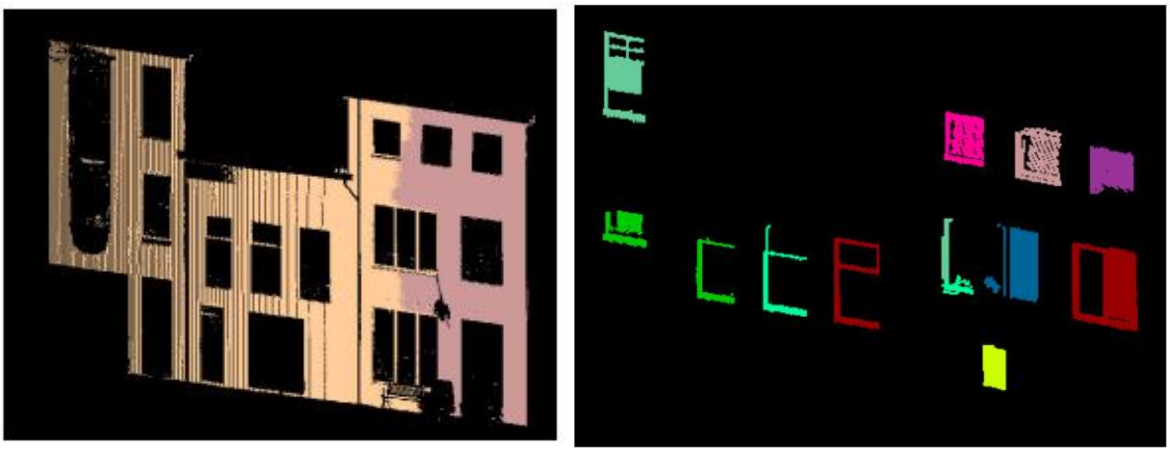


Figure 1: Recognized features (left: wall, right: windows)

Table 2: Recognition quality (Pu et al. 2006)

	Total number	Recognized number
Ground	1	1
Wall	1	1
Window	11	7
Roof	3	3
Door	5	5
Protrusion	3	3
Intrusion	0	0

Ground, wall, roof, door and protrusion are all very well recognized, while only 7 of 11 window features are correctly recognized. This difference in recognition rate is mainly due to the different segmentation quality. The planar surface growing algorithm always starts with a seed surface, which is a group of nearby points that fit well to a plane. In the growing phase points are added to the seed surface, if the distance of a point to the plane is below some threshold. The plane parameters are updated after every added point, so the larger the plane the more reliable the plane parameters will be. That is why large features such as ground or wall will generate more reliable surfaces.

The paper (Awrangjeb et al. 2013) presents a new segmentation technique for point cloud data for automatic extraction of building roof planes. Using the ground height from a DEM (Digital Elevation Model), the raw points are separated into two groups: ground and non-ground points. The ground points are used to generate a 'building mask' in which the black areas represent the ground where there are no laser returns below a certain height. The non-ground points are segmented to extract the planar roof segments. First, the building mask is divided into small grid cells. The cells containing the black pixels are clustered such that each cluster represents an individual building or tree. Second, the non-ground points within a cluster are segmented based on their co-planarity and neighborhood relations. Third, the planar segments are refined using a rule-based procedure that assigns the common points among the planar segments to the appropriate segments. Finally, another rule-based procedure is applied to remove tree planes which are small in size and randomly oriented. The described methodology is represented in Figure 2 below:

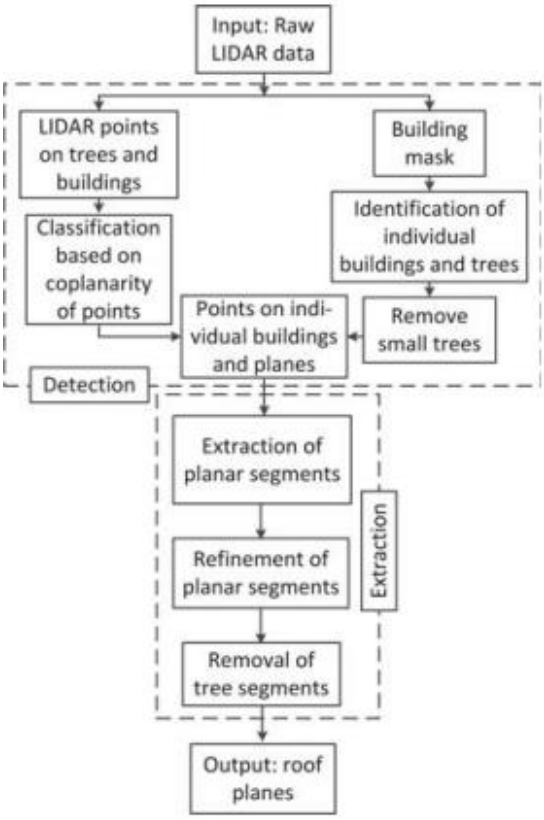


Figure 2: Methodology for building roof planes extraction (Awrangjeb et al. 2013)

The Vaihingen (VH) data set from the ISPRS benchmark test (Rottensteiner et al. 2012) has been used in an experimental assessment and validation of the proposed roof plane extraction approach. There are three test sites. Area 1 is characterized by dense development consisting of historic buildings having complex shapes. Area 2 is characterized by a few high-rise residential buildings surrounded by trees. Area 3 is purely residential with detached houses and many surrounding trees.

Figure 3 shows the roof plane extraction results for Area 1:

Figure 3: Roof extraction results (b) on Area 1 of the VH data set

For all three areas, there were many under-segmentation cases where small roof structures could not be separately extracted, but might be merged with the neighboring large planes, and some low height roof structures were missed. However, due to use of point cloud data only, the plan metric accuracy of the proposed method is limited by point cloud density. Boundaries of the extracted planar segments are not smoothed. Future work could focus upon an integration of the available imagery with the LIDAR data. The integration of image data will also help for better object extraction where LIDAR information is missing (Awrangjeb et al. 2013).
In the Table 3 is presented accuracy, ie. plan metric and height error in meters for all three areas.

Table 3: Accuracy of obtained results (Awrangjeb et al. 2013)

Areas	Plan metric accuracy [m]	Height error [m]
VH 1	1.05	0.41
VH 2	0.74	0.37
VH 3	0.89	0.27
Average	**0.89**	**0.35**

Yang et al. (2012) present a method for automated extraction of street-scene objects from point cloud. The proposed method first generates the georeferenced feature image of point cloud and then extracts the boundaries of street-scene objects, such as buildings. The method of image segmentation and contour tracing on the georeferenced feature image generated is applied. The same authors also provided a comprehensive discussion of parameter selection for generation of georeferenced feature images for different purposes (e.g., building extraction and power-line extraction). The proposed method was adopted to generate a georeferenced feature image of point cloud. Figure 4 shows a result of suggested approach.

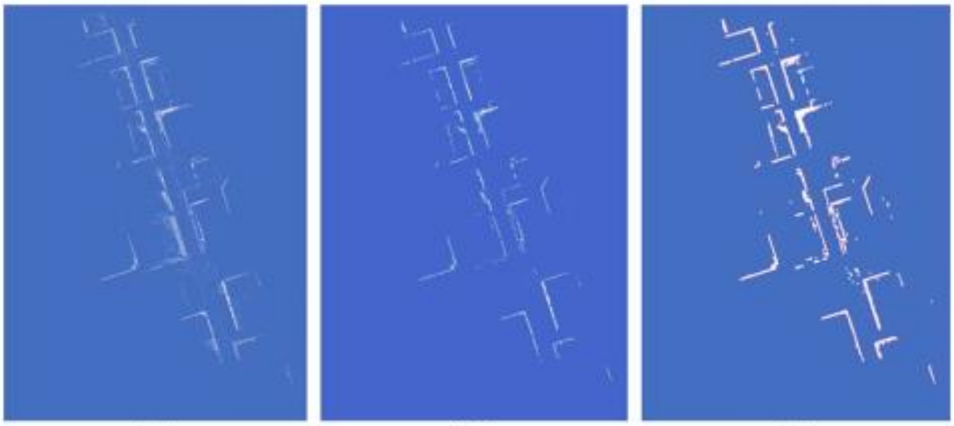

(a) (b) (c)

Figure 4: Segmentation and contour extraction of a georeferenced feature image.
(a) Original image. (b) Segmented image. (c) Extracted contours

The authors of paper (Yang et al. 2013) proposes a coarse-to-fine approach which automatically and effectively extracts building facades from point clouds in urban environment. The proposed method involves generation of georeferenced feature images of point clouds, image processing of the generated georeferenced feature images, identification of building objects, coarse extraction of facades and refinement of these facades.

Once the contours of man-made objects have been extracted, the spatial extent of each object can easily be calculated. Then, according to the calculated spatial extent, the point cloud corresponding to each object can be extracted. As the extracted objects from contours could be buildings or trees, the building objects should first be isolated for extracting facade footprints. It is difficult to directly distinguish between buildings and trees by gray values in the segmented georeferenced feature image. However, points of buildings and trees show notable differences on spatial distributions in 3-D space. Also, the extracted facade footprints of one building may be disjoint because of occlusion or incomplete extraction. To connect disjoint footprints, a virtual intersection vertex is generated according to the interrelationships among the footprints of the building. The extracted footprints can thus be connected and harmonized.

Three data sets of downtown and residential areas captured by the LYNX mobile mapping system were selected to verify the validities of the proposed method. The spatial span of the captured point cloud is approximately 1–5 cm. The numbers of points in data sets *testdata-1*, *testdata-2*, and *testdata-3* are 8 318 968, 10 447 105, and 8 139 726, respectively. The spatial extents of the data sets are approximately 410 m $*$ 560 m, 550 m $*$ 750 m, and 400 m $*$ 350 m, respectively. Table 4 and Figure 5 show an overview of all test data and proposed methodology results (Yang et al. 2013).

Table 4: Results of building identification for the three data set

	The number of ground-truth objects			Identification of buildings and trees		
	multi-storey buildings	residential buildings	trees	multi-storey buildings	residential buildings	trees
Testdata-1	30	0	0	30	0	0
Testdata-2	34	1	0	34	1	0
Testdata-3	0	50	3	0	52	1

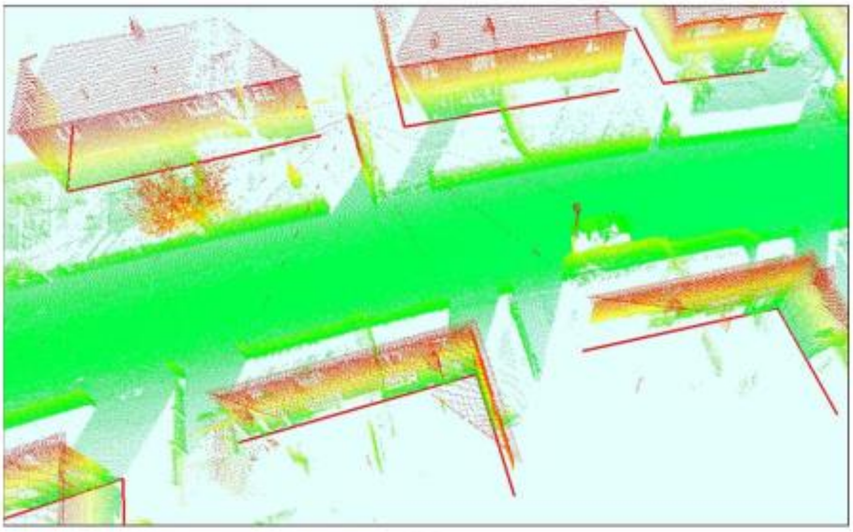


Figure 5: Matched extracted facade footprints and original point cloud (Yang et al. 2013)

The achieved results appear encouraging and demonstrate that the proposed method provides an effective solution for extracting building facade footprints from point cloud data. Reflection intensities of point cloud and associated imagery will be incorporated for better point-cloud mapping and understanding, which will improve the extraction of facade footprints (Yang et al. 2013). However, the fact is that the footprint extraction of buildings which have cylindrical facades and even more complex structures still needs further study.

3. ROAD EDGE AND ROAD MARKING EXTRACTION SOLUTIONS

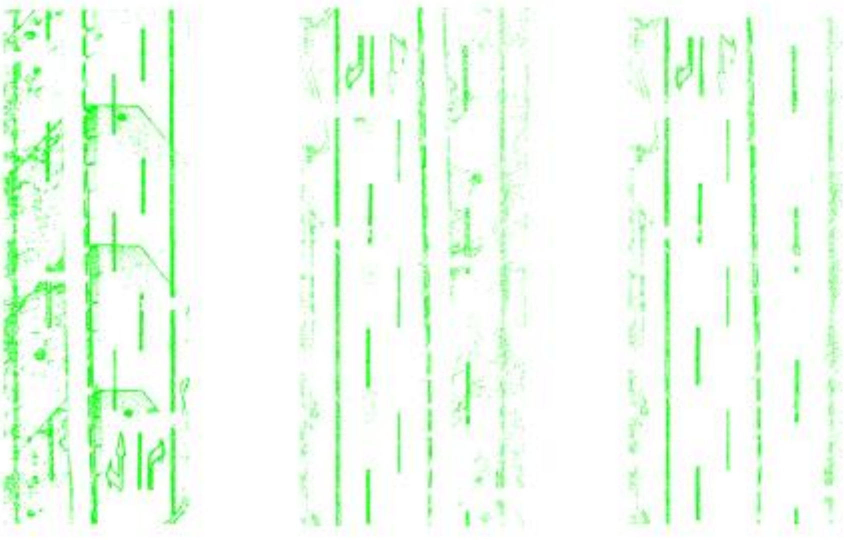
Road information is one of the most important parts of basic geographic information. An accurate and high-precision road information plays an important role in urban planning, traffic control, and emergency response (Fang et al. 2013). In this chapter are presented some new approaches regarding road marking and road edges automatic extraction, by using point cloud data.
A few studies have been published on the extraction of road markings. Fang et al. (2013) classified three types of roads and built a digital road model with three indexes: height, point

cloud density and slope. They extracted structural road information by analyzing the spatial distribution of point cloud and statistical characteristics of the laser scan lines. But, it turned out that this algorithm cannot be applied to different fields.

Hernández et al. (2009) determined the road boundary by the elevation change and differences along the cross-section of the studied road. The hypothesis of this study is that the road surface should be on the same elevation and should be relatively even. However, owing to the different objectives of algorithm design and the low accuracy of the extraction results, all of the mentioned research extracted road information rather than road markings. That makes this approach not so much broadly-applied.

The author Gao et al. (2017) presents a novel method process to automatically extract road markings using multiple attribute information of the laser scanning point cloud from the point cloud data. This method process utilizes a differential grayscale of RGB color, laser pulse reflection intensity and the differential intensity to identify and extract pavement markings. The point cloud density is utilized to remove the noise and morphological operations are used to eliminate the errors.

In the application, proposed method is tested on different sections of roads in Beijing, China, and Buffalo, NY, USA. This research used the data collected by the SSW Vehicle Borne Mobile Model system. The scanning range of data was roughly 2000 m × 300 m, with an approximate point number of 20 million. Figure 6 shows the results of the original point cloud after being extracted by proposed algorithm. Afterwards, the point cloud data were vectorized.



(a) (b) (c)

Figure 6: Extraction results using: (a) adjacent point cloud gray level differential; (b) point cloud intensity value and intensity difference; and (c) dynamic grid point cloud density filtering (Gao et al. 2017)

The results indicated that both correctness and completeness were higher than 90%. The method process of this research can be applied to extract pavement markings from huge point cloud data produced by MMS.
Beside road marking, road edges extraction is very important. It can be useful in many branches, such as road registration, road reconstruction, traffic management. The authors of paper (Xia et al. 2017) propose a new method for extracting edges in the original 3-D mobile lidar point cloud. The method consists of two steps, edge detection and linking. In the first step, a new edge detector based on geometric centroid is proposed and edge candidates are detected by analyzing eigenvalues. In the linking step, a graph snapping algorithm is proposed to obtain smooth edge segments. Finally, the proposed method is evaluated on various scenes and a test in large-scale street scenes is also conducted.
To evaluate the proposed method, MMS point clouds acquired by Optech Lynx SG1 system along urban street with average density around 1500 points/m² were used. All the involved algorithms are implemented in C++ and experiments were conducted on a computer with Intel Core i7-6700HQ 2.6-GHz CPU and 16.0-GB RAM.
Fig 7 shows original data., ie. point cloud and results of proposed methodology. Based on the edge definition, manually counted edges were used as ground truth. According to authors paper (Xia et al. 2017), curbs are extracted with precision of 82.5 %.

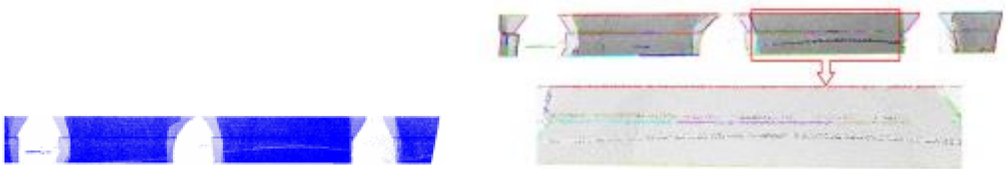


Figure 7: Original data and results of the proposed method paper (Xia et al. 2017)

4. STREET LIGHT POLES EXTRACTION SOLUTIONS

As an essential component of the transportation infrastructure, street light poles function to provide vehicles and pedestrians with illumination at night. Cost-effectively monitoring and managing street light poles are important to the transportation management department.
According to the design and construction manuals for street lighting systems, light poles always have predefined shapes, heights, and sizes that provide essential prior knowledge for the detection and extraction of the light poles. This chapter focuses right on street light poles detection and extraction approaches.
A percentile based algorithm was introduced in (Pu et al. 2011) for the recognition of light poles. Instead of analyzing the whole object segment, the segment was first divided into four quartiles. Considering the impact of the shrubs attached at the bottom of a light pole, as well as other attachments to the pole, such as traffic signs and advertising boards, the third quartile was selected and divided into horizontal slices. Finally, light poles were recognized based on the detection of vertical pole-like structures.

In (Hu et al. 2011), a density of projected points algorithm was applied to extract street light poles from point cloud. First, point cloud was divided into voxels on the XY plane. Then, the maximum height of each voxel was calculated and a height threshold, based on the height data, was subsequently determined. Finally, by classifying point cloud into ground, low ground and high ground points, light poles were extracted by applying the height threshold.
In the paper (Yu et al. 2015) is proposed a novel algorithm for segmenting road surfaces and extracting street light poles from mobile LiDAR point-clouds. This algorithm is carried out based on the following stages:

1) a series of road profiles is generated along the vehicle's trajectory,
2) curb lines are extracted based on profile analysis and then used to segment the point cloud into road and non-road surface points,
3) ground points are further removed from non-road surface points using a voxel-based elevation filter,
4) the filtered point cloud is clustered into groups based on a Euclidean distance clustering method,
5) the clusters that contain more than one object are further segmented using a normalized cut segmentation method,
6) light poles are finally extracted using a novel pairwise 3-D shape context, which is defined for modeling the geometric structure of a 3-D point cloud object.

Following those steps, specific area of point cloud is chosen, and methodology is conducted. The first mobile LiDAR data were acquired in Xiamen, China. The survey was carried out on Ring Road South, which is a two-directional–four-lane road with a median separating the direction of travel, and covered a total distance of approximately 60 km. Light pole extraction results on those areas are presented in Figure 8.

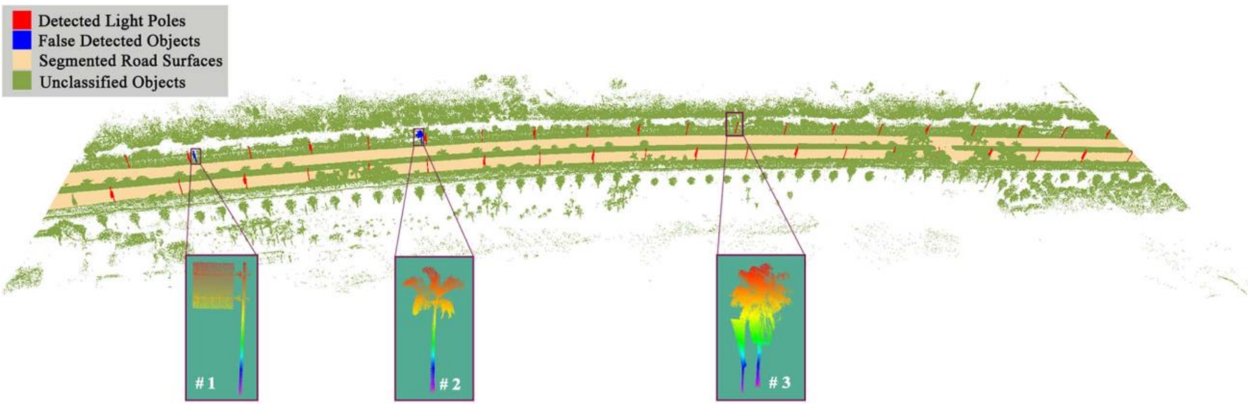


Figure 8. Road surface segmentation and light pole extraction results from data set-I (Yu et al. 2015)

This methodology has a lot of advantages, such as true positives rate and quality of final result. Anyway, there is still space for further development, regarding detection of other pole-like objects on street, such as masts, traffic lights and signals.

CONCLUSION

In the past two decades, LiDAR technology has rapidly developed and been used to acquire geospatial information for a variety of applications: urban planning, environmental impact assessment, cultural heritage documentation, intelligent transportation systems, and disaster management. This system provides an efficient solution for capturing spatial data in a fast, efficient and highly reproducible way. Thus, accurately extracting objects from mobile LiDAR point cloud has attracted more and more attention in different branches.

Nowadays, there are a lot of methodologies for obtaining objects of interest. The focus is on improving existing methodologies regarding speed, quality, precision and level of details. A key issue is to identify geometric features (for example, the boundary of a building) automatically. Compared with the capturing of mobile LiDAR data, which is straightforward, the processing of these data urgently requires powerful and effective solutions for purposes such as emergency mapping, feature extraction, data fusion, and 3-D reconstruction. That is why the need for detailed 3-D information about buildings continues to increase steadily.

This article has presented a novel solutions regarding this topic. It can be concluded that automated extraction of spatial entitites from MMS data is still a challenging task, although extensive efforts have been made in this area.

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BIOGRAPHICAL NOTES

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