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Road Surface Extraction from MLS-Based Point Clouds

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ABSTRACT

Mobile mapping technology is one of the most commonly used technologies to collect three-dimensional spatial data. Geomatics engineering is the one discipline that used this technology the most. These systems are used extensively in which laser scanning systems are integrated, especially in corridor mapping purposes. In this study, it is proposed to extract the road surface automatically from Mobile LiDAR-based point clouds. The proposed methodology consists of three steps: (1)collecting MLS raw data; (2) producing three-dimensional dense point cloud; (3) classifying ground/non-ground point filtering and applying a piecewise linear regression model to extract the road surface. As a result, the proposed methodology successfully extracts the road surface from the MLS-based point cloud.

1. INTRODUCTION

Advanced Driver Assistance System and autonomous transmission technology are clearly among the hottest topics among existing transportation systems. Self-driving vehicles will become widespread in the near future, and millions of these vehicles will be on the road (Yao, Chen, Qin, Wu, & Zhang, 2018). High resolution three-dimensional (3D) maps will be primary sources to actively provide essential information to 3D dynamic self-driving vehicles, rather than just being static maps tracking a city's development. In addition, the signs on the road are essential for providing guidance and information to drivers and pedestrians (Soilan, Justo, Sanchez-Rodriguez, & Riveiro, 2020). This will also be important for high-resolution 3D transportation.

There are many measurement technologies available today to produce high-resolution 3D maps (Neupane & Gharaibeh, 2019). Laser scanning is one of the widely used technologies to produce high-resolution 3D maps. Every visible object can be digitized with high resolution in laser scanning.

Mobile LiDAR System (MLS) is a technology that collects 3D dense information around the road while platforms move at average speeds on the road (Yadav & Singh, 2018). Dense point cloud information is a widely used measurement technique with its high accuracy and reasonable price.

3D dense point cloud provides essential information in various research areas such as extracting the road surface, analyzing the road geometry, drive simulation, road maintenance studies, and self-driving autonomous vehicles (Wu, Xu, & Liu, 2019). However, MLS point clouds often contain irregular and noisy points. The 360-degree measurement of the MLS technology also makes it difficult to extract the road surface from the 3D dense point cloud. In addition, further difficulties are encountered in detecting the road surface from MLS point clouds. The irregular and noisy dense point cloud make data pre-processing difficult. Another difficulty is that the traffic flow might be intense and causes both interruptions on road surfaces and an increase of false point in point clouds. Therefore, the road surface extraction from MLS point clouds is an open research field for improvement.

In this study, an accurate and efficient method is presented to automatically extract the road surface from MLS point clouds. Our study's primary steps can be summarized into three steps: 1) collecting MLS data in normal traffic flow, 2) producing 3D dense point cloud in the pre-processing step, 3) introducing a new automated approach to extract road surface points from MLS point clouds.

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The proposed pipeline starts with a pre-processing step to convert the raw data into a dense point cloud. With the help of the trajectory data, non-road scene points, such as buildings and fences, etc. are removed. That is, the number of points is decreased to improve the accuracy and reduce the processing time. Then, non-ground points are removed by applying the cloth simulation filtering (CSF) algorithm (Zhang et al., 2016). Finally, the points of the road surface are extracted using the piecewise linear regression model.

2. MATERIAL AND METHODS

Data was collected using the RIEGL VMX-450 system in Konya, Turkey. The MLS system is shown in Figure 1(a). The VMX-450 system includes tools such as two RIEGL VQ450 laser scanners, four optional RGB cameras, a GNSS antenna, an IMU system, and a distance measurement indicator. In the GNSS/IMU system-based measurements, a fixed RTK reference station, whose x, y, and z coordinates were known, was installed, and the GNSS system on the vehicle was made to receive corrections with this RTK reference station. An example of the scanned study area is shown in Figure 1(c). The proposed method has been conducted on an 80 m long study area. The flowchart of the proposed method is presented in Figure 2.

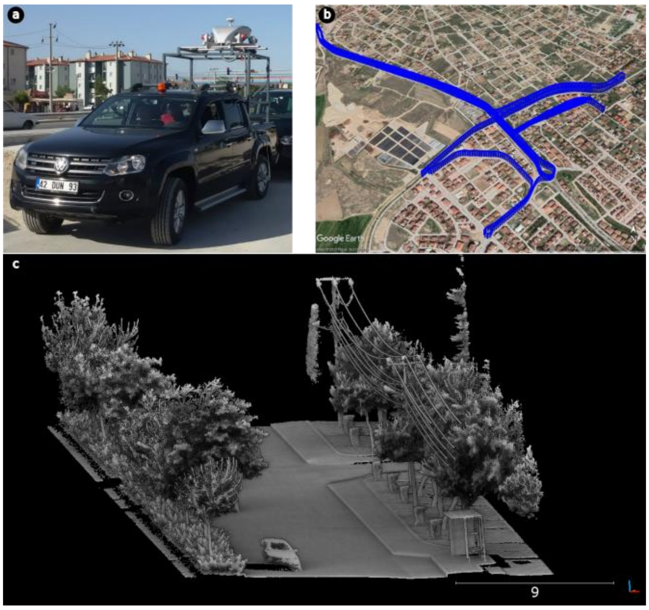

Figure 1. a) VMX-450 MLS system, b) trajectory, and c) acquired point cloud data.

2.1. Pre-Process

Applanix POSpac software was used to obtain 3D dense point cloud from collected MLS raw data. Processed point clouds were exported in las file format. In order to reduce the processing intensity and the processing time of the proposed method, a 20 m buffer zone covering the road and the road environment was created with the trajectory data provided by the point clouds VMX-450 system. The trajectory data of this study is presented in Figure 1(b). Then, the points that are outside the buffer zone are removed. The buffer threshold should be determined specifically for the road being measured. Wider roads might require larger buffer threshold values. After this pre-processing, both the number of points in the point clouds decreased, which leads to the short processing time for the proposed method.

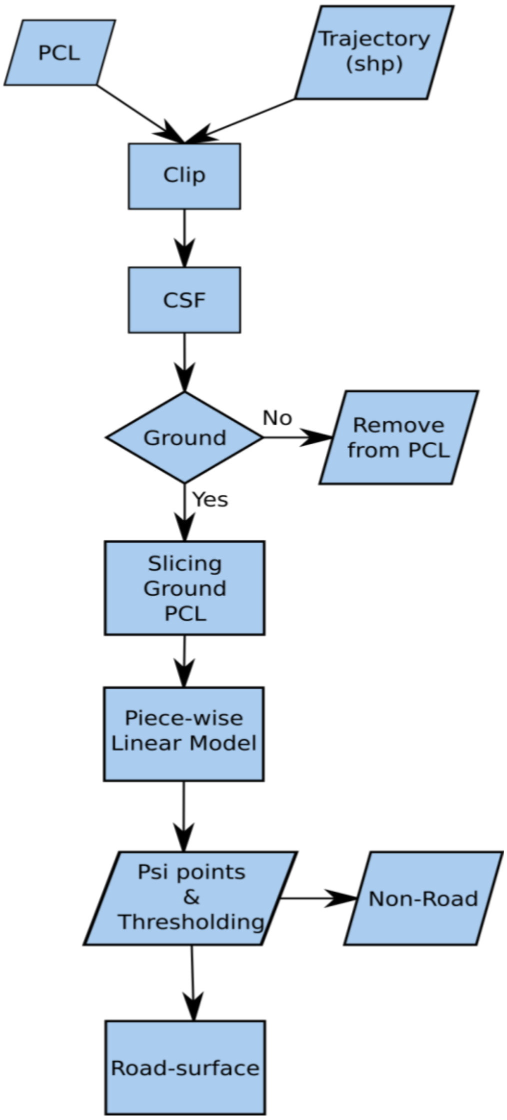

Figure 2. Flowchart of the proposed methodology.

2.2. Methods

In the proposed method, first point clouds are classified as ground and non-ground. The main reason for this step is that the road surface has to be on ground points. The cloth simulation filtering (CSF) algorithm was used for ground and non-ground classification (Zhang et al., 2016). This algorithm is based on the principle of reversing the point clouds concerning the *Z*-axis and covering with the cloth on it. In this way, points intersect with cloth grids are assigned as ground and non-intersecting points as non-ground. Figure 3 presents the ground and non-ground classification results. The point clouds are divided into cross-sections at 1 m intervals according to GNSS trajectory values. In this study, original coordinates are transformed using principal component analysis (PCA) to prevent errors and provide straightforward interpretation in cross-sectional analysis.

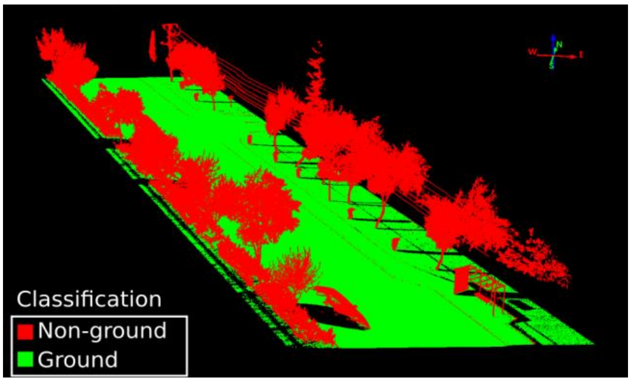

Figure 3. CSF-based point cloud classification.

PCA is one of the essential methods for multivariate data analysis (Bruce, Bruce, & Gedeck, 2020). PCA's primary purpose is a dimensional reduction and a commonly used method for calculating linear variables (components). In this study, PCA has been used to calculate a new coordinate system, which is orthogonal and uses only the most fundamental dimensions. Thanks to crucial components from PCA, distances between spatial variables are presented clearly. Figure 4(a) and (b) present the single cross-section with original coordinates and coordinates obtained from PCA, respectively. Finally, road points were extracted by applying piecewise regression over the cross-section points represented by PCA.

Piecewise linear model is a regression model where more than one straight line is fitted (Muggo 2003). These lines are connected to unknown values, which are usually called breakpoints. The piecewise linear relationship between response variable Y and independent variable X_i for observations i = 1, 2, …., n can be defined as follows:

$$Y_i = \boldsymbol{\beta}_1 X_i + \boldsymbol{\beta}_2 (X_i - \boldsymbol{\psi}) \quad [1]$$

where $\boldsymbol{\beta}_1$ is the left slope, $\boldsymbol{\beta}_2$ is the difference between slopes, and $\boldsymbol{\psi}$ is the breakpoint. $(X_i - \boldsymbol{\psi})$ is equal to $(X_i - \boldsymbol{\psi}) \times I(X_i > \boldsymbol{\psi})$ where I(.) is the indicator function equal to one when the statement is correct. Several software packages estimate the piecewise linear regression model given the data and the number of breakpoints (V. M. Muggeo, 2003). In this study, R software was used to estimate the parameters and breakpoints (Vito MR Muggeo, 2017; Team, 2019).

3. RESULTS

There were 5,434,846 points after converting MLS raw test data into a point cloud using Applanix POSpac software. The number of points decreased to 4,096,144 when removing non-essential points using GNSS Trajectory and 20 m buffer value. Then, the CSF algorithm was used to classify ground points, and 3,138,305 ground points were filtered. The point cloud was divided into cross-sections according to orthogonal to the GNSS/Trajectory data using the R software (in-house developed "slicer" package). 80 cross-sections of 1 m width were produced in this study. Figure 5 shows several cross-sections as an example. Finally, points representing the road surface were extracted using the piecewise linear model on these cross-sections.

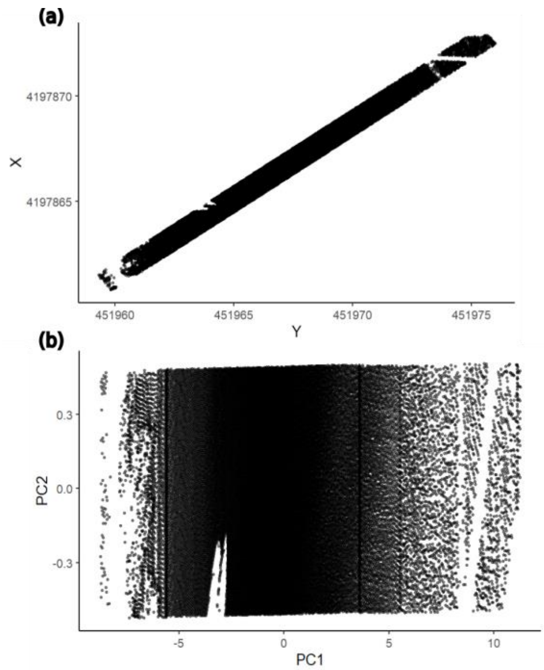

Figure 4. PCA employment on cross-sectioned data a) cross-section raw data, b) PCA transformed data.

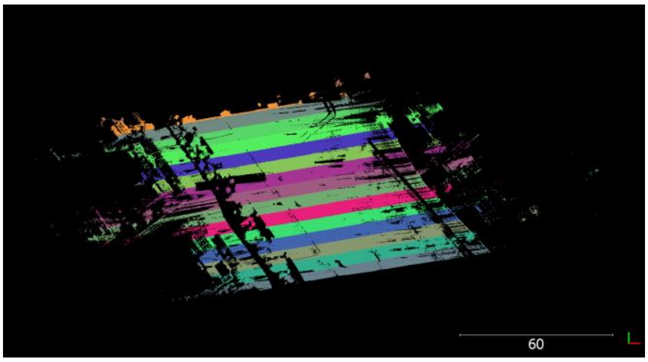

Figure 5. Cross-sections according to GNSS/Trajectory on Slicer R codes

The number of breakpoints (psi) to be predicted on the piecewise linear model is given as an input parameter. This value can be used to estimate the best fit in the cross-section data. In cases where psi value is not taken as input, the variable is assumed to be 1. Figure 6 shows the points, and the piecewise linear model results under different psi values. As the number of breaking points increases, the piecewise linear model fits better. Distance-threshold values are defined from these breaking points. Finally, points in between these distance-thresholds are extracted as the road surface—the extracted road surface points estimated as road surface 32,188 points from a single section (40,766).

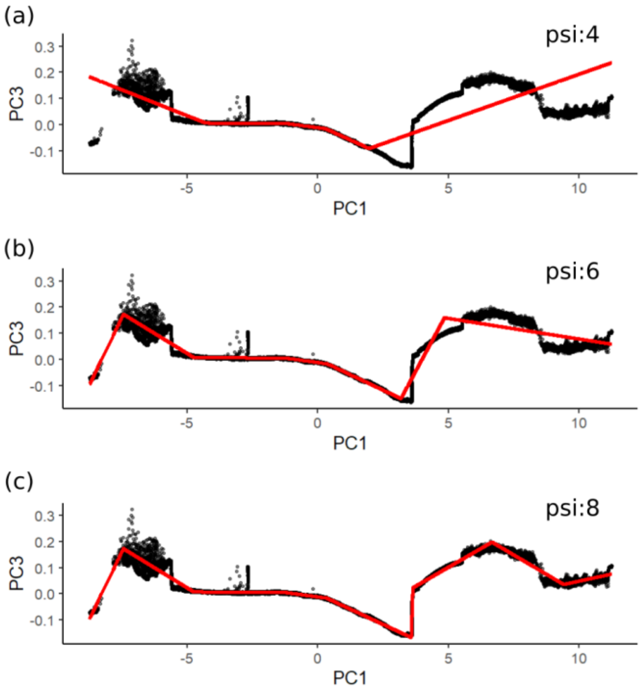

Figure 6. Piecewise based linear model on the cross-sectional model.

4. DISCUSSION

The orthogonal components of the cross-sections can be improved by using robust PCA methods. The main reason for this is that the PCA method is sensitive to outliers. Outliers are common in dense point cloud data obtained from Mobile LiDAR, and these values overestimate conventional measures of variance. The outlier's points will be in different directions than the directions since the PCA components follow their maximum variance direction. The piecewise linear method is proposed to extract the road surface with the number of breaking points as an input. Then, a distance-based threshold is defined from these breaking points. Under different road geometric conditions, the threshold values may need to be revised to accurately extract the road surface. Therefore, it is better to estimate psi breakpoints automatically in future studies. Besides, leverage points on the piecewise linear model are likely to occur regardless of psi breakpoints. In this case, it is necessary to determine and delete these outlier points from the point cloud with a distance-based threshold value or the clustering algorithms such as DBSCAN or connected component algorithms.

The proposed methodology has been developed for roads with raised curbs in urban areas. Its effectiveness has not been tested on rural roads or roads without a raised curb. Therefore, this method should be tested on different Mobile LiDAR data in a future study.

5. CONCLUSION

In this study, it is proposed to extract the road surface automatically from Mobile LiDAR-based point clouds and GNSS/Trajectory data. The Piecewise linear model algorithm was fitted using the points, and the road surface was extracted from the breakpoints in the road segment. The proposed methodology is an alternative and effective method for extracting the road surface using the mobile LiDAR data.

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