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AUTOMATIC GROUND EXTRACTION FOR URBAN AREAS FROM AIRBORNE LIDAR DATA

Sibel Canaz Sevgen *[1] and Fevzi Karsli [2]

[1] Ankara University, Faculty of Applied Sciences, Department of Real Estate Development and Management, Ankara, Turkey
ORCID ID 0000-0001-5552-6067
ssevgen@ankara.edu.tr

[2] Karadeniz Technical University, Engineering Faculty, Geomatics Engineering Department, Trabzon, Turkey
ORCID ID 0000-0002-0411-3315
fkarsli@ktu.edu.tr

ABSTRACT

Terrain models play a key role in many applications, such as hydrological modeling, volume calculation, wire and pipeline route planning as well as many engineering applications. While terrain models can be generated from traditional data sources, an advanced and recently popular geospatial technology, Light Detection and Ranging (LiDAR) data, is also a source for generating high-density terrain models in the last decades. The main advantage of LiDAR technology over traditional data sources is that it generates 3D point clouds directly so that the representation of the surfaces is obtained fast. On the other hand, before terrain modeling, ground points need to be extracted by point labeling in the 3D point cloud. In this study, a new algorithm is proposed for automatic ground point extraction from airborne LiDAR data for urban areas. The proposed algorithm is mainly based on height information of the points in the dataset and labels ground points comparing height differences in local windows. The algorithm does not require any user input threshold and a neighborhood definition. The proposed ground extraction algorithm was tested with three different urban area LiDAR data. The quality control basically performed qualitatively by visual inspection and quantitatively by calculation of overall accuracy, which is conduct by comparing the proposed algorithm results with data provider's ground classification and Cloth Simulation Filtering (CSF) algorithm's results. The overall accuracy of the proposed algorithm is found between 95%-98%. The experimental results showed that the algorithm promises reliable results to extract ground points from airborne LiDAR data for urban areas.

Keywords: Ground Extraction, LiDAR, Ground Modeling, Urban Area, Remote Sensing

1. INTRODUCTION

LiDAR has been gaining its popularity as a remote sensing technique in recent decades in many areas. It has become a main data source of many applications in many engineering fields, such as machine learning, pattern recognition, data mining and knowledge extraction. The advantage of LiDAR is that it requires less effort to have 3D data with respect to traditional data sources. Airborne LiDAR system is generally mounted on an aircraft and assisted with Global Positioning System (GPS) and Inertial Navigation System (INS) systems. 3D dense point cloud data accurately collected by basically sending a laser pulse from a transmitter and receiving the scattered back photons. Using the travel time between signal emission and reception 3D point cloud data is created. Airborne LiDAR data has been being used by many researchers especially for feature extraction and ground modeling & DTM generation applications (Liu 2008; Chen *et al*. 2017). To extract features such as building, trees etc. and/or create ground models firstly separation between ground and non-ground has to be implemented. So that, extracted ground points can be employed for terrain modeling and Digital Elevation Model (DEM) generation. DEM studies are also widely used which are created using LiDAR data (Büyüksalih and Gazioğlu, 2019). Particularly, ground extraction and modeling are important in terms of usage for model water flow, planning applications, classification of objects, volume calculation and other applications (Canaz Sevgen, 2019; Yılmaz and Uysal, 2017).

Ground can shortly be described as a solid surface of the earth while non-ground represent the objects that do not belong to the ground or pertaining to the ground surface. Extraction of the ground surface and generating a model from LiDAR data with filtering algorithms were studied by many researchers (Kraus and Pfeifer 2001; Liu and Zhang 2008; Yuan *et al*. 2009; Wang and Tseng 2010; Mongus and Zalik 2012, Mongus *et al*. 2014, Uysal and Polat, 2014; Zeybek *et al*., 2015). In literature, filtering algorithms for ground modeling can be classified into groups such as interpolation-based (surface-based) filtering algorithms (Kraus and Pfeifer 1998; Chen *et al*. 2007; Lee and Younan 2003), Sloped-Based filtering algorithms (Vosselman 2000; Zhang *et al*., 2003), Morphological Filtering algorithms (Kilian *et al*. 1996; Lohmann *et al*. 2000; Zakšek and Pfeifer 2006), and Segmentation-Based Filters (Filin and Pfeifer 2006; Tovari and Pfeifer 2005).

Point-cloud data also can be generated from photographs (Akçay *et al*., 2017). In recent years, some researchers also studies ground extraction to create digital terrain models from point clouds generated from photogrammetric aerial photographs instead of using LiDAR data. For instance, Yilmaz *et al*. (2018) investigates the performances of seven widely used ground filtering algorithms from commercial and non-commercial software's on UAV-based point clouds. Wallace *et al*. (2016) another example of UAV-based point cloud filtering algorithm investigation study. Zeybek and Şanlıoğlu (2019) filtered UAV-based 3D raw point cloud data and compared four different filtering algorithms; curvature based (Multiscale Curvature Classification-MCC), surface-based filtering (FUSION), progressive TIN based (LasTool-LasGround

module-commercial) and physical simulation processing (Cloth Simulation Filtering-CSF). Wang *et al*. (2014) also filtered Point Cloud Extracted from UAV Images. Point clouds generated from aerial photographs are dense comparing with LiDAR data; however, in some cases it is not possible to create point clouds from photograph since creating point clouds needs overlapping images. More specifically, in contrast to laser scanning, 3D data can be only derived from overlapping imagery whenever conjugate features have been identified and the intersection of the respective spatial rays is mathematically described (Canaz and Habib 2013). Therefore, in this study source of the data was chosen as LiDAR.

On the other hand, some researchers created ground filtering algorithms by focusing on ground extraction from LiDAR data on urban areas. Urban areas are abundant on non-ground objects, which means that sudden height differences occur in these areas such as ground to building facades, or roof of buildings and cars. In view of the fact that urban areas have more non-ground object compared with the bare territory, many researchers developed algorithms to extract ground on urban areas. For instance, Shan and Sampath (2005) extracted ground for urban areas performing a forward and backward labeling algorithm, which uses slope and elevation difference, and they created DEM for urban areas from airborne LiDAR data. Wang and Zhang (2016) extracted ground points by utilizing the scan line information in LiDAR data and using similarity measurement. Furthermore, a combination of slope based method and region growing was studied for ground extraction from LiDAR data in urban areas by Feng *et al*. 2009. Three windows with different sizes; small, average and large are created and a height difference threshold, was used for separating ground and non-ground points in each local window by Rashidi and Rastiveis (2017). Meanwhile, the best threshold values for the size of windows are considered based on physical characteristics of the ground surface and size of objects. In this study, the algorithm is proposed to not have any threshold entered by users. Hence, the proposed algorithm does not require any user input threshold to label and extract ground points.

Recently, a Cloth Simulation Filter (CSF) algorithm was developed by Zhang *et al*. (2016) for generating DTM from point cloud data. The authors firstly turning point cloud upside to down, and then rigid cloth is used to cover the inverted surface. Their algorithm analyzes the cloth nodes and the corresponding LiDAR points` intersection. Finally, the generated surface are compared with the original surface for extracting the ground points from the LiDAR point cloud. In this study, the proposed algorithm's ground extraction result was compared with the CSF algorithm results.

An elevation based algorithm for separation of ground and non-ground points for urban areas from airborne LiDAR data was proposed in this study. The algorithm cuts the large area of LiDAR data to into small windows size and then height difference for each point to randomly selected points were calculated. The number of below and upper points label the point as ground or non-ground. The algorithm based on that ground points generally do not have lower points from them. Most advantageous part of the proposed algorithm is that it does not require any threshold entered by the

users, and separate ground and non-ground points without any user interference. The proposed algorithm was tested with three different datasets, which differ from each other in point density, vegetation density, and building data type, The result of the proposed algorithm was compared with data provider's ground classification, which was performed by LAStools and TerraScan LiDAR processing software package, and the CSF algorithm (Zhang *et al*. 2016) ground extraction results. The proposed algorithm gives reliable results for extracting ground points from LiDAR data for urban areas according to the comparison result.

2. METHODOLOGY

Urban areas generally have dense non-ground objects such as trees, buildings, cars etc. For these areas, airborne LiDAR data consist of points which are scattered back from both ground points and any points which belong to non-ground points. Starting from this point, the proposed algorithm was developed to extract ground points from LiDAR data automatically for urban areas by simply using ground points and non-ground points height differences. The details of the methodology are explained in next sections.

To extract ground points from raw LiDAR data of an urban area, an algorithm was proposed, and a stepwise approach was followed. The proposed algorithm firstly start with creating *n* number of *m* by *m* meters sized windows of LiDAR data. In this study, 30 meters windows were chosen since mainly in urban areas 900 m² are enough to present non-ground points of objects and ground points. If there are no non-ground points (i.e. cars, trees, buildings) in the window area, the algorithm assigns all the points as ground points by simply

checking height differences in the current window. The proposed algorithm firstly performs windows creation, and using points in the windows, classification of non-ground and ground points from LiDAR data was performed. The algorithm firstly, creates *n* number of 30×30 meters windows in XY planimetric space.

The proposed algorithm mainly have one condition. The condition is that non-ground points in the current window area higher than ground points. To calculate heights differences, firstly for each point to randomly selected points, distances are calculated in the Z axis. The points are randomly selected to prevent compare height distance from only same classes (ground/non ground) then, a number of height distances less than zero and more than 1 meters is counted. In other words, a number of positive and negative distances are counted for each point. Since LiDAR data standard deviation in Z axis generally changes 10 cm to 1 meter (Liu, 2011), 1 meter is intentionally chosen to prevent counting points which are in the same class and very close to each other. For instance, in LiDAR data points which are on the ground have generally 10 cm to 1 meters height differences even if they are in the same plane, and this is occurring because of LiDAR data nature. So that, to not count these point for positive distance 1 meter was intentionally chosen. After that, minimum height in the current window is found and used to check labeled ground points if they are too high than the local height, the point checked again if it is non-ground points by using the other labeled ground points.

The proposed algorithm lay on a logic, if a positive number of distance points more than the negative number of distance points, then the point is assigned as non-ground points. Since non-ground points are higher than ground points in the window size area (Fig. 1).
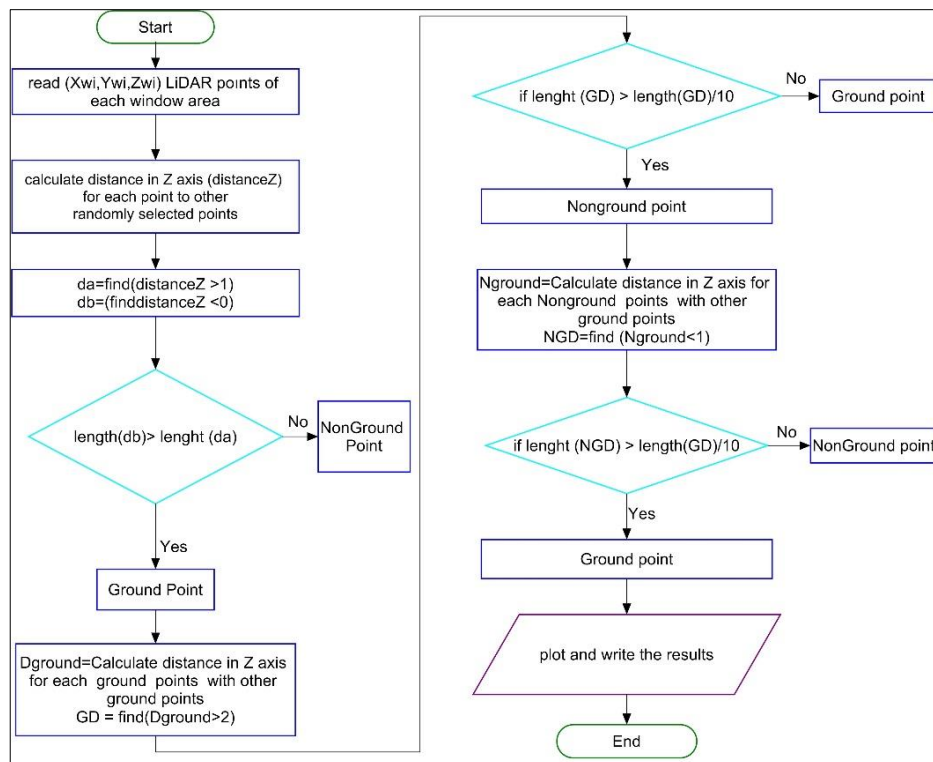

Fig. 1. Flowchart of the proposed methodology

The logic behind the proposed algorithm is illustrated in Fig. 2. In the figure red point is the selected as a sample point. Blue points represent non-ground points, while ground points are displayed as green. For the red point, if distance higher than 0 and less than 1

meter is calculated with randomly selected points, there will be more number of points that are higher than red points. Therefore, the red point will be assigned as ground point.
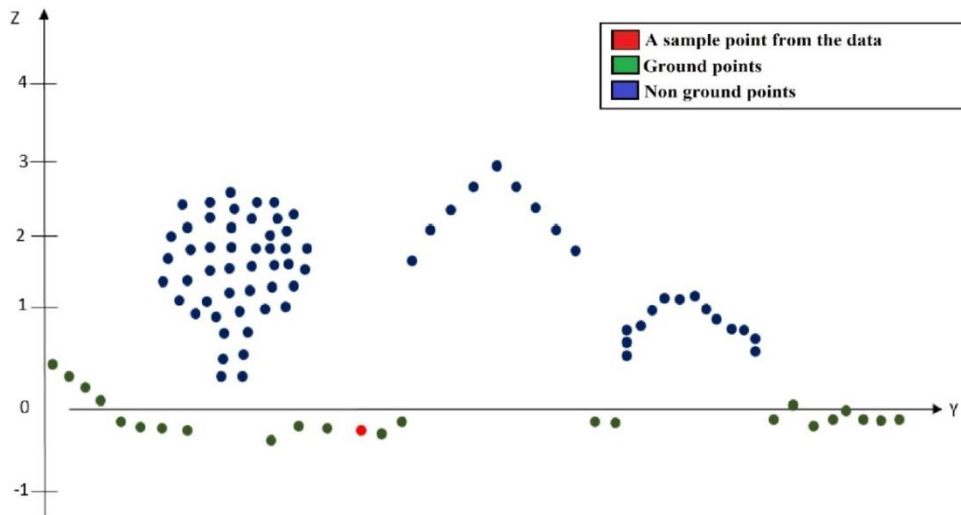

Fig. 2. Illustration of the condition for the proposed algorithm

After the proposed algorithm assigns ground and non-ground points, a quick quality control was employed to check the points labeled correctly. The control starts with a calculating distance of each assigned ground point to other ground points. If the distance from a ground point to other ground points have much distance in Z, the ground point is assigned as non-ground points and it will be removed from ground point class. The logic behind this calculation is that in the window size data, ground points should not have such a huge height difference even in the sloped areas.

For the final analysis of the results, quality controls were applied. Firstly visual inspection was carried out. The visual quality control is simply performed by plotting and comparing the classified ground and non-ground points with the plotted reference. Reference ground extraction was employed by data provider which conducted by using LAStools and TerraScan LiDAR processing software package and the CSF algorithm. LAStools classify ground basically using Adaptive Triangulated Irregular Network (ATIN) algorithm (Axelsson, 2000). A search windows are created and angle criteria was used to classify ground points in LAStools. According to visual inspection, the proposed algorithm gives reliable results, which can be seen in the results section in the figure of results.

On the other hand, quantitative quality control was performed by comparing each point's classes with reference classes. The proposed algorithm labels points 0 and 1 as non-ground and ground points, respectively. After sorting reference and the proposed algorithm result and reference classes according to X, Y and Z axes, the classified points and reference point's classes (i.e. the CSF algorithm's results) were compared one by one. For the quantitative quality control, error matrices were

created and overall and producers' accuracy were calculated. The details of the quality control are discussed in the results section in details.

3. RESULTS AND DISCUSSION

The proposed ground extraction algorithm was tested with three different dataset which contain only urban areas. The first data set is downloaded from a package of a LiDAR processing tool *LAStools* (2017) and the data is called as *Fusa* in this study (*https://rapidlasso.com/lastools/)*. Reference Ground Classification of *Fusa* data set was already conducted by *Lastools* software package. The data contains approximately 277K points. The total area of the data is 0.06 km². The second data used in this study is from Istanbul (Bimtaş Co., Istanbul) and named as *Istanbul* hereafter. The area of *Istanbul* data is 0.37 km² and total number of points is 1.8M. The third data is from California U.S. (obtained from Digital Mapping, Inc. (DMI), U.S.) It has 1M points and its area is 5.23 km² (Table 1). Reference Ground Classification of *Istanbul* and *California* was employed by data provider using TerraScan software. The details of the data can be seen in Table 1. *California* data set's area is bigger than *Fusa* and *Istanbul* data area, while these two data sets are denser compared with *California* data set. Furthermore, *Istanbul* data sets have taller buildings comparing with *California* and *Fusa* data sets, while *Istanbul* has less tree in contrast to the two other data sets. Aforementioned proposed algorithm partitions the data into 30×30 meters window in XY plane, and a total number of windows for each dataset is given in Table 1.

Table 1. LiDAR data sets' details

Data Name	Number of Points	Ave. Point Density	Dimensions (m)	Area (km^2)	# of Windows (30×30 m)
Fusa	277,354	4.44	249X249	0.06	**81**
Istanbul	1,845,761	4.93	534X700	0.37	**432**
California	1,023,432	0.19	2729X1918	5.23	**5,824**

Ground/non-ground classification points in the Fusa data set's result is shown in Fig. 3. Fig. 3a is the classified reference data set by LAStools software package, Fig. 3b is the proposed algorithm's classification results, Fig. 3c is the CSF algorithm result. The green area of the figure represent the ground points, while red points are non-ground points (buildings, cars, trees etc.)
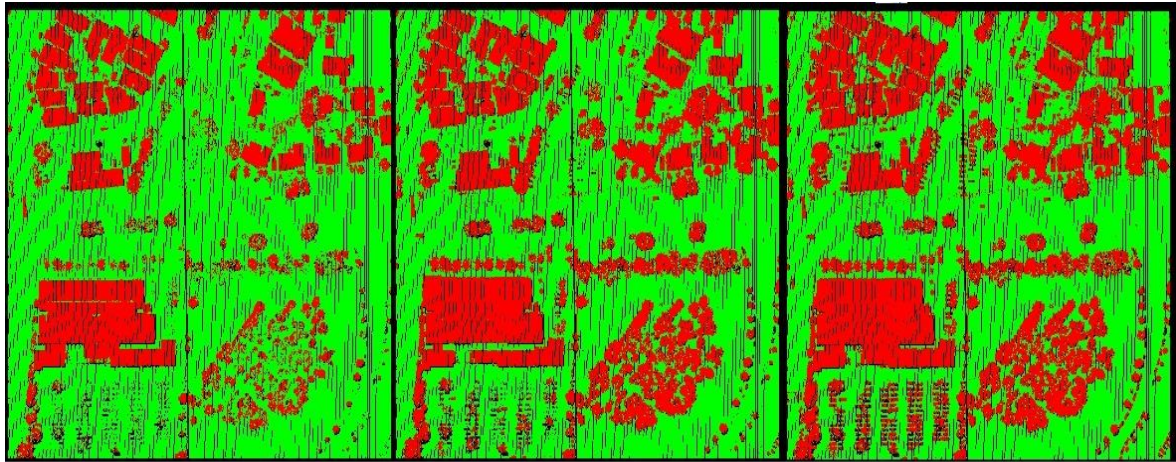

Fig. 3. Ground extraction result for Fusa data sets. (a) data provider classification result (Lastools), (b) the proposed algorithm result, (c) the CSF algorithm result.

To evaluate result visually, the study area for the Fusa data set given in the below (Fig. 4). According to the below images, and the results above, it can be said that all the classification results are correctly labeled by comparing the images and the results.

Fig. 4. Ortophoto images for Fusa data sets (Source: Google web services)

To examine result visually, randomly selected part of the areas from the result was zoomed and showed in Fig. 5 for Fusa data set. Fig. 5 has also 3D view of the

closer examined results. Left columns are 2D views of the selected parts (XY plane), and right columns are their 3D representation. Upper selected part of the result has both trees and houses as non-ground objects, while bottom part includes only trees as non-ground objects. According to visual inspection of the result, it can be easily observed that the algorithm worked very well, and ground points are successfully extracted.
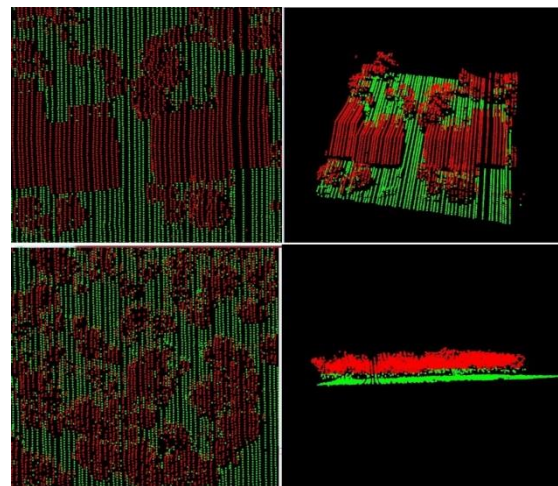

Fig. 5. Closer examination of ground/non-ground classification result of Fusa data set by proposed algorithm

Istanbul data set classified ground and the non-ground result is illustrated in Fig. 6. Fig. 6a shows classified ground and non-ground points in reference

data, whereas Fig. 6b is the result of the proposed algorithm, and Fig. 6c is the CSF algorithm result. It can be easily observed that the proposed algorithm gives very reliable results, by comparing Fig. 6a, 6b, and 6c. Ground points are successfully extracted from the whole Istanbul LiDAR data set.
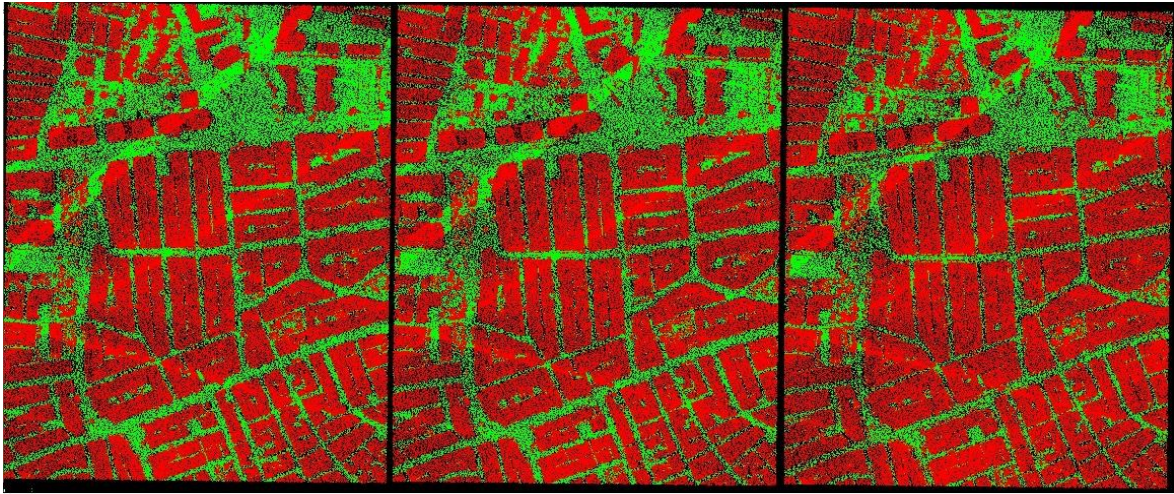

Fig. 6. Istanbul data set results; (a) data provider classification result (by TerraScan), (b) the proposed algorithm result, (c) the CSF algorithm result.

Orthophoto imagery of the Istanbul data set area is shown in Fig. 7, the buildings can be easily seen in the image, and these buildings and non-ground area were successfully classified by the proposed algorithm (Fig. 6b)

from the result in 2D coordinates system (XY axes), right columns are their 3D view. Istanbul data has very tall building and it is observed that the proposed algorithm work very well with data sets that have tall non-ground objects.

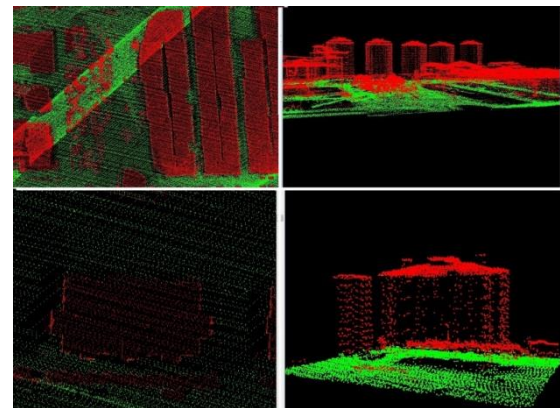Fig. 7. Orthophoto images for İstanbul data sets

For qualitative quality control, randomly chosen areas are zoomed and shown in Fig. 8 from Istanbul data set result. Here again, left columns are selected areas

Fig. 8. Closer examination of ground- non-ground classification result of Istanbul data set

Finally, the result for the California data set can be seen in the below (Fig. 9). As mentioned before, red areas represent non-ground points of the data. The area is large and has very big size houses in contrast to two previous data sets. The result for the proposed algorithm represented in Fig. 9b.

Fig. 9. California data set results; (a) data provider classification result (by TerraScan), (b) the proposed algorithm result, (c) the CSF algorithm result.

The study are for the California data set shown in the below orthophoto image, as it can be seen in the image, the area has so many houses, and the area is slightly complex. However, overall it can be observed that the proposed algorithm was extracted ground reliable by comparing the Fig. 10 and Fig 9b.

Fig. 10. Ortophoto images for California data sets (Source: Google web services)

Fig. 11 is an example of closer examination from results in California data set and it shows how the proposed algorithm gives reliable results. Upper left figure includes results of non-ground points (houses) and big size ground part, and its 3D view can be seen on the right upper part in the figure. On the other side, bottom figure is an example of non-ground that includes tree and houses. According to visual closer quality control. Only a few points were wrongly labeled in these randomly selected part of the result.
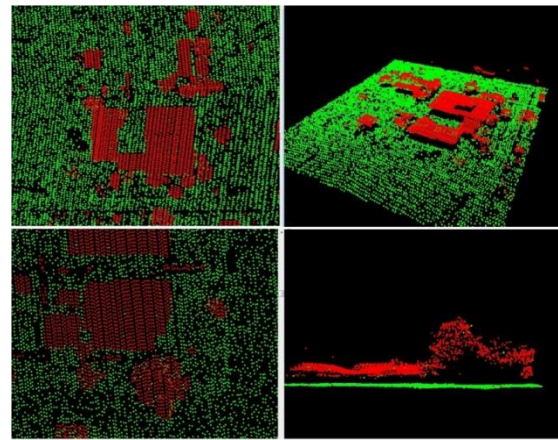

Fig. 11. Closer examination of ground- non-ground classification of California data set result

The results from the proposed algorithm were compared with reference result qualitatively and quantitatively. Qualitative evaluation is carried out by visual interpretations of the results. Nevertheless, a quantitative evaluation is conducted by calculating overall accuracy and producer's accuracy. To conduct quantitative quality control, error matrix is created. Table 2 shows the error matrices and total accuracy as well producer's accuracy (1) and (2).

$$Overall_{Accuracy} = \frac{Exracted\ (Ground+Non-ground)}{Total\ points} x100 \quad (1)$$

$$Producer's_{Accuracy} = \frac{Extracted\ Ground\ or\ Non-G\ Points}{Total\ Ground\ or\ Non-ground\ Points} x100 \quad (2)$$

Table 2 Error matrices for the proposed ground extraction algorithm versus reference result

Fusa	Ground Points	Non-ground Points	Total reference
Ground Points	191475	6785	198260
Non-ground Points	1000	78094	79094
Total Proposed Algorithm	192475	84879	277354
Producer's Accuracy (%)	96.58	98.74	Overall Accuracy= 97%
Istanbul Area	**Ground Points**	**Non-ground Points**	**Total** reference
Ground Points	681405	25894	707299
Non-ground Points	194	1138268	1138462
Total Proposed Algorithm	681599	1164162	1845761
Producer's Accuracy (%)	96.33	99.98	Overall Accuracy= 98%
California	**Ground Points**	**Non-ground Points**	**Total** reference
Ground Points	471448	6374	477822
Non-ground Points	44769	500841	545610
Total Proposed Algorithm	516217	507215	1023432
Producer's Accuracy (%)	98.66	91.79	Overall Accuracy= 95%

According to the quantitative quality control for the proposed ground extraction algorithm, overall accuracy is calculated 95%, 97%, 98% for California, Fusa and Istanbul, respectively. According to quantitative quality control, it can be said that the algorithm gives reliable results for extraction of the ground points automatically in urban areas.

Finally, the proposed algorithm ground/non-ground extraction was compared with the CSF algorithm result. The overall accuracy was observed between 95-97%. Producer's accuracy was found between 90-99%.

Table 3 Error matrices for the proposed ground extraction algorithm versus CSF Results

Fusa	Ground Points	Non-ground Points	Total CSF
Ground Points	183495	183	183678
Non-ground Points	8980	84696	93676
Total Proposed Algorithm	192475	84879	277354
Producer's Accuracy (%)	99.99	90.41	Overall Accuracy= 97%
Istanbul Area	**Ground Points**	**Non-ground Points**	**Total CSF**
Ground Points	587186	7076	594262
Non-ground Points	94413	1157086	1251499
Total Proposed Algorithm	681599	1164162	1845761
Producer's Accuracy (%)	98.80	92.45	Overall Accuracy= 95%
California	**Ground Points**	**Non-ground Points**	**Total CSF**
Ground Points	465816	5502	471318
Non-ground Points	50401	501713	552114
Total Proposed Algorithm	516217	507215	1023432
Producer's Accuracy (%)	98.83	90.87	Overall Accuracy= 95%

4. CONCLUSIONS

In conclusion, terrain modeling and creating DEM have vital importance in the usage of hydrological modeling, telecommunication industry etc. 3D data is necessary to create terrain modeling. LiDAR technology have the ability to collect 3D data fast and directly using laser pulses. Since LiDAR advantage of the dense 3D data set, it was chosen as the main dataset for this study. An algorithm was proposed to extract ground and non-ground points from LiDAR data in the urban areas. In

the literature there are many algorithms that extracts ground points, while automatically study of extraction of the ground points are limited for the urban areas. The most advantageous of the proposed algorithm is that it does not require any threshold input and extract the ground/non-ground points automatically using the height difference of the point with the randomly selected other points in urban areas. The algorithm was tested with three different LiDAR data sets, and the results were compared with the data provider reference ground points and the CSF algorithm result. Error matrices were

created overall accuracy is calculated between 95-98%, while producer's accuracy calculated as 86-99%. Furthermore, qualitative quality control carried out simply plotting inspecting the reference data and the proposed algorithm results visually. According to both qualitative and quantitative quality control, it is observed that the proposed algorithm gives reliable result in urban areas. Consequently, the algorithms extract ground points in the urban area from LiDAR data set automatically. The most advantage part of the proposed algorithm is that it is fully automated. For the future work, the algorithm will be developed for the areas that does not only include urban areas.

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