ROOF PLANE DETECTION AND COMPARISON OF POINT CLOUDS ACQUIRED BY DIFFERENT DATA SOURCES USING RANSAC ALGORITHM

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ABSTRACT:

Solar energy is a renewable energy source directly from sunlight and its production depends on roof characteristics such as roof type and size. In solar potential analysis, the main purpose is to determine the suitable roofs for the placement of solar panels. Hence, roof plane detection plays a crucial role in solar energy assessment. In this study, a detailed comparison was presented between aerial photogrammetry data and LIDAR data for roof plane recognition applying RANSAC (Random Sample Consensus) algorithm. RANSAC algorithm was performed to 3D-point clouds obtained by both LIDAR (Laser Ranging and Detection) and aerial photogrammetric survey. In this regard, solar energy assessment from the results can be applied. It is shown that, the RANSAC algorithm detects building roofs better on the point cloud data acquired from airborne LIDAR regarding completeness within model, since aerial photogrammetric survey provides noisy data in spite of its high-density data. This noise in the source data leads to deformations in roof plane detection. The study area of the project is the campus of Istanbul Technical University.

1. INTRODUCTION

In the recent past, the interest in accurate and detailed 3D building data acquired by airborne LIDAR systems has been growing. Building Information Modelling (BIM), snow load capacity estimating and modelling and solar potential analysis can be given as examples of application areas for building detection (Jochem et al., 2009b). Today, solar energy can be produced on the rooftops of private houses as easily as in energy companies after detecting proper building roofs.

Building reconstruction is applied by algorithms generally on planar surfaces. However, a fundamental issue which has not been completely solved occurs in building detection. The data from laser scanning measurements taken in city area mostly includes noise and incompleteness caused by tree points or reflection (Huang et al., 2011).

In this contribution, a comparison of aerial photogrammetry and LIDAR data in roof plane detection presented with completeness values of each data source. The main aim of this contribution is evaluating two different data inputs and concluding which data is superior to another in the aspect of accuracy, correctness and completeness.

2. DATA AND METHODOLGY

2.1 Study area

Study area of the project is located in Istanbul Technical University-Ayazaga Campus. Building Arı 1 was selected on both aerial images and LIDAR point clouds to apply the algorithm. Besides single buildings and block buildings, the study area contains small objects such as cars and vegetation types.

2.2 Data

In the study, two distinct data sources were used: LIDAR data and aerial photogrammetry data.

2.2.1 Airborne LIDAR data

The airborne LIDAR point cloud was obtained using a laser scanning system. The horizontal and vertical accuracy of the LIDAR data are about 8 cm. Average point density of the data is 16 points/m^{-2}.

2.2.2 Aerial photogrammetry data

For taking aerial photographs, DJI Phantom 4 Pro was used. The UAV has a sensor with a calibrated focal length of 3.61 mm. The following flight parameters were selected: Forward-overlap and side-overlap is respectively 80% and 70%. The

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UAV was flown at a height of 80 m. In total, 288 high resolution images were acquired from the flight. Approximately a GSD (Ground Sampling Distance) of 3 cm/pixel was obtained.

2.3 RANSAC algorithm

RANSAC (Random Sample Consensus) algorithm developed by Fischler and Bolles (1981) is a method to create appropriate solutions of mathematical models in iteration processes. Parameters corresponding to the mathematical model are defined before iteration process. A consensus solution is obtained as the best result (Carrilho and Gallo, 2018).

Number of trials k can be calculated by:

$$k = \frac{\log(1\text{-}z)}{\log(1\text{-}(1\text{-}w^{n}))} \tag{1}$$

In the equation 1, n is the minimum number of points which is required for the calculation of the corresponding model. Since minimum 3 points can define a plane, n is equal to 3 in the case of planar models. Probability z is a minimum probability value of finding at least one proper set of observations in N iterations. z is usually in the range between 0.90 and 0.99. w is the probability of observations allowed to be incorrect (in percentage).

During the iteration process, algorithm is performed many times and corresponding data set is removed from the original point cloud. The next iteration continues on the remaining points. Finally, iteration is terminated when the number of non-modelled points is smaller than defined threshold (Kurdi et al., 2008).

An essential advantage of RANSAC algorithm is that number of trials and data size are not directly dependent on each other. Thus, iterations can be quickly obtained on even high-density point clouds (Carrilho and Galo, 2018).

Other advantages of RANSAC algorithm are listed below:

- Its concept is simple to apply
- It is a general algorithm and used in a wide variety of applications
- It can robustly work, even if the data includes more than 50% of outliers (Schnabel et al., 2007).

3. APPLICATION

A software, namely Agisoft Photoscan, was utilized to create a dense point cloud from the aerial images. Dense point clouds were created using 20 aerial images.

A height threshold was defined for classification of objects depending on the Z coordinates. In fact, the points below a predefined height threshold were eliminated from original data to separate ground and non-ground points. For dataset Arı 1, threshold values were determined on dense point cloud and LIDAR data, respectively: 60 and 93 m.

RANSAC parameters used in the code are the followings:
z is a scalar value of the noise standard deviation. *P_inlier* (default vale of P_inlier = 0.99) is a Chi-squared probability value for inlier points. *T_noise_squared* is error threshold that overrides sigma, when it is provided. *Max_iters* (default = 0) is the maximum number of iterations allowed and *min_iters* (default = ∞) is the minimum number of iterations required.

Sigma, P_inlier, min_iters and T_noise_squared are accepted as 0, 1000, 0.99 and 0.0016, respectively.

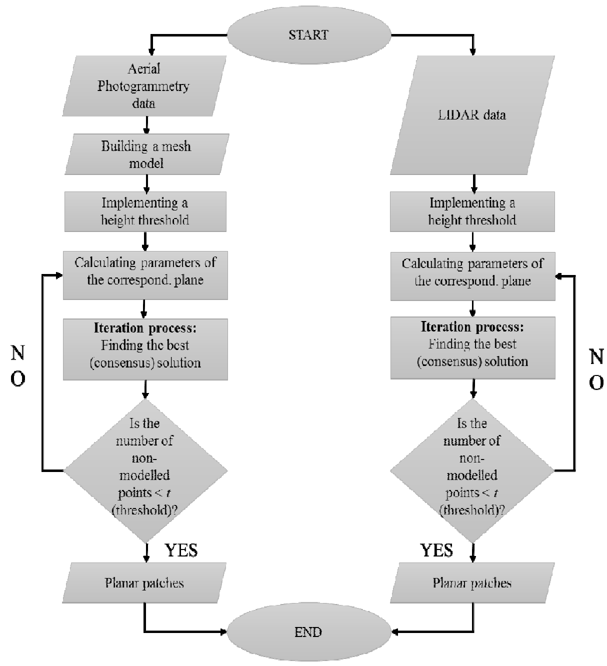

Figure 1: Flowchart of the proposed roof plane extraction method

4. RESULT AND DISCUSSION

As shown in the following figures, roof planes were extracted separately for LIDAR and aerial photogrammetric data by using RANSAC algorithm. The results from different data sources were compared to each other regarding their error, accuracy, correctness, completeness, by calculating confusion matrix of each plane. The values of reference class were manually calculated on both LIDAR and aerial photogrammetric data.

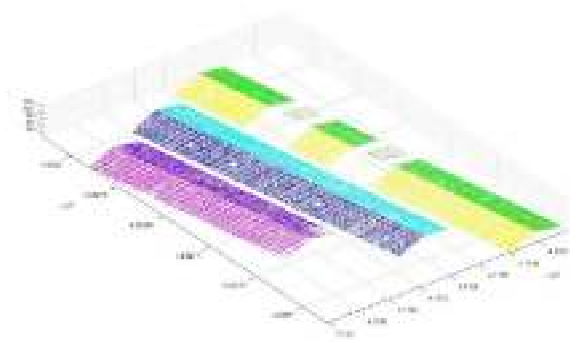

Figure 2: Detected roof plane from LIDAR data

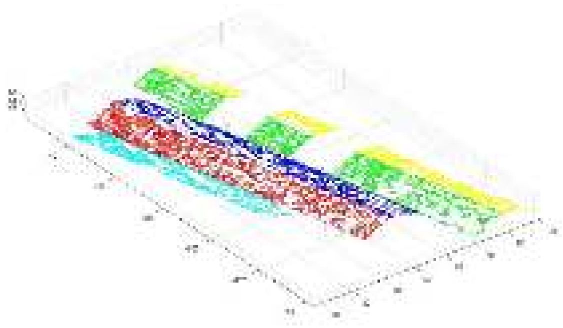

Figure 3: Detected roof plane from aerial photogrammetry data

Table 1. shows confusion matrix containing True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) values.

	Detected model class		
True class (Reference)	Positive	Negative	Total
Positive	True Positive (TP)	False Negative (FN)	p
Negative	False Positive (FP)	True Negative (TN)	n
Total	p’	n’	N

Table 1: Confusion matrix for two classes (Alpaydin E., 2010).

TP: True Positive refers to plane points which are included inside the detected model.
TN: True Negative refers to non-plane points which are outside the detected model.
FP: False Positive refers to plane points which are not included inside the detected model.
FN: False Negative refers to non-plane points which are included inside the detected model.

Error, accuracy, correctness, completeness of the detected plane model can be easily derived from the confusion matrix values. Formulas of the values are mentioned below (Alpaydin E., 2010).

$$\text{Error} = \frac{\text{FP+FN}}{\text{N}} \tag{2}$$

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{N}} = 1\text{-error} \tag{3}$$

$$\text{Correctness} = \frac{\text{TP}}{\text{TP+FP}} \tag{4}$$

$$\text{Completeness} = \frac{\text{TP}}{\text{TP+FN}} \tag{5}$$

The following tables indicate a result of the proposed method. In the results, error means the probability of incorrectly detected points in total. In contrast to error, accuracy refers to the probability of correctly detected points in total. Correctness is the probability of correctly detected plane points. Completeness means how many points that are detected as plane points are plane points in the reality.

Some planes were not detected by using dense point cloud from aerial images. Because there are many tree points on the rooftops and those points cover a part of roof planes. But, on the LIDAR data, all the planes were extracted without any problem.

According to the results above, RANSAC algorithm extract more completed model planes on LIDAR data. Because dense point cloud created by aerial photogrammetry produces noisier data. Noisy data can lead to incompleteness in model. But, LIDAR data has more error which means how many point in total are mistakenly detected.
Accuracy value which means how many points in total are correctly detected is usually better on dense point cloud data. Also correctness value which means how many plane points are correctly detected is also better on dense point cloud data, in contrast to LIDAR data.

Arı 1	**TP**		**TN**		**FP**		**FN**	
	Aerial p. data	**LIDAR data**	**Aerial p. data**	**LIDAR data**	**Aerial p. data**	**LIDAR data**	**Aerial p. data**	**LIDAR data**
1	13834	16937	61325	8887	28	478	35801	21188
2	12378	16988	64533	8349	340	572	32593	21726
3	11664	16949	60127	8472	265	404	36999	21603
4	9630	15272	64361	9238	117	571	32765	20837
5	7855	11268	76574	7464	286	595	20552	22611
6	-	-	-	-	-	-	-	-

Table 2: Confusion matrix values of Arı 1 dataset

Arı 1	Error		Accuracy		Correctness		Completeness	
	Aerial p. data	**LIDAR data**	**Aerial p. data**	**LIDAR data**	**Aerial p. data**	**LIDAR data**	**Aerial p. data**	**LIDAR data**
1	32 %	46 %	100 %	97%	100 %	97%	46 %	68 %
2	30 %	47 %	97 %	97 %	97 %	97 %	47 %	70 %
3	34 %	46 %	98 %	98 %	98 %	98 %	46 %	66 %
4	31 %	47 %	99 %	96 %	99 %	96 %	47 %	69 %
5	20 %	55 %	96 %	95 %	96 %	95 %	55 %	80 %
6	-	-	-	-	-	-	-	-

Table 3: Error, Accuracy, Correctness and Completeness of Arı 1 dataset

5. CONCLUSION

In recent years, a lot of algorithms have been developed which detect roof planes. RANSAC algorithm which is one of the most used algorithms on LIDAR data to extract mathematical shapes is represent in this study for a comparison of between aerial photogrammetry and LIDAR data. However, as a main result of this study, data source is very important for successful roof plane detection. In block buildings, algorithm has difficulties to find plane points correctly. It is concluded that irregular shapes of the roofs are not successfully detected. Moreover, tree points or ground points can negatively affect the roof plane detection.

In future studies, larger roof planes can be preferred for better accuracy analysis. For aerial photogrammetry data, more photos should be used. Because, the planes acquired by aerial photogrammetry have many gaps on the rooftop plane. These gaps could be filled with the help of more aerial photographs and completeness value could be increased in this manner.

Reference class can be defined according to other criteria in forthcoming studies. Defining a reference class manually like in this study can cause incorrect classification of points. Taking into account the results of the study, laser data and optical data can be integrated and used together, since they complement each other.

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