LANDSLIDE MONITORING AND ASSESSMENT FOR HIGHWAY RETAINING WALL: THE CASE STUDY OF TAŞKENT(TURKEY) LANDSLIDE

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ABSTRACT:

Landslide monitoring and assessment of the highways retaining walls are a crucial task. Because there exist a risk and danger with regard to the movement of the wall to the highway by landslide force that may spread further. To evaluate the changing, movements have to be monitored. For this reason, we practised mobile LiDAR surveys on the landslide effected wall on the highway. The usage of the mobile LiDAR systems have significantly increased in recent years, especially for road management. Currently, mobile LiDAR technology is capable of measuring the earth surface with high precision and density as a 3D point clouds. As stated in this study, the point cloud data processing have been analysed further and the wall surface points fitted to a plane object for monitoring of the landslide effects. This study focuses on different plane fitting algorithms which represents the retaining wall, a performance assessment and evaluation of the deformation between two plane models. The analysis indicates that the uncertainty of the measurements between the two epochs on stable areas survey was within ± 2 cm. According to the experimental results, the proposed methods performed promising results that can be used for monitoring of retaining walls for fast processing and assessment.

1. INTRODUCTION

Retaining walls are constructed mostly for holding the soil mass on highway constructions to be retained at different levels on the road sides. They are used to hold soils on high or undesirable slopes inside mountainous roads due to the difficulties of road design. Retaining walls are also supporting structures planned to keep under the control of the landslide materials at landslide regions. The difficulties of monitoring landslides are occurring when the terrain is complex, time consuming operations and workforce. Furthermore, it is rather quite difficult to do measurement in flowing traffic and raises the risk. The survey of geometric characteristics of the wall construction is made to verify the stability from the landslide destructive effect and to guarantee a health of the walls. The survey of the wall surface characteristic is done with regard to allow highway traffic safety condition. Deformation shifts and cracks of the wall are should be examined carefully. In particular the evaluation of the surface roughness has acquired a remarkable importance in control activities of the wall structure and in monitoring.

Light Detection And Ranging (LiDAR) surveying techniques enable to acquisition of an accurately georeferenced set of dense 3D point clouds (Canaz and Habib, 2014, Canaz et al., 2015, Erbas, 2016). The surface changing studies are possible to identify displacements when two or more surface models generated from different point cloud source such as airborne (ALS), ground (TLS) or mobile lidar systems (MLS). LiDAR based surveys are able to measure vertical faades or slopes excluding the ALS (Karabacak et al., 2011). TLS and MLS surveys reach a centimetre as a survey grade on positional accuracy for ground deformation studies (Wang et al., 2011, Julge et al., 2017).

Particularly, a Mobile LiDAR measurement system (MLS) which is the combination of a Global Navigation Satellite System (GNSS), an Inertial Measuring Unit (IMU) and LiDAR scanners on a moving vehicle, makes possible effective and complete 3D data collection (Wang et al., 2014, Kumar et al., 2014). Urban object changings can be detected automatically from MLS generated point cloud on complex street environment (Xiao et al., 2013).

Recent researches have examined for monitoring walls with photogrammetric methods which are one of them that create 3D spatial data information about surfaces. Lately, improvements in a computing and graphical processing have allowed digital photogrammetric methods to be of comprehensive use (Oats et al., 2017). However, traffic or highway standards do not allow for measurements on road, due to the time consuming for productivity. In this study, we have examined of mobile LiDAR technique are examined for retaining wall monitoring.

1.1 Objectives of the study

To increase the reliability and the quality of the landslide analysis, the observed point clouds have to be created as a geometric model. Outliers have been considered in LiDAR observation points which is far away from other observations on the plane. Generally, measurement limitations of the sensor, 3D features on wall surface like rocks and concretes, multiple reflectances can produce off-wall and noisy surface points that also appear to be outliers. Local outliers mostly cannot be guaranteed to filter out from point clouds (Sotoodeh, 2006). We aim to find coherent plane parameters which cannot lead to an inconsistent and misleading result from noise and outliers. Robust regression method which is introduced by (Huber et al., 1964) is mostly used estimation technique for various disciplines. Proposed method is improving the robust estimators. Robust regression M-estimator based algorithm implemented in this paper to construct retaining wall for monitoring of deformation between two point cloud data.

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1.2 Landslide area

The landslide region at Taşkent where is a province of Konya in Turkey, was selected for the implementation of the landslide retain wall displacement analysis since the incessantly events of mass movements at this region (Figure 1). The highway is connecting the provinces and towns in southern part of middle Taurus mountain chain. It is the linking way for the six towns through Taşkent.

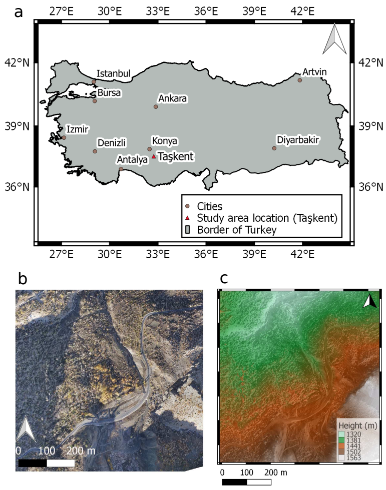

Figure 1. Location of the study area a) Location of Taşkent province in Turkey, b) UAV derived Orthomosaics, c) Digital surface model.

2. MATERIAL AND METHODS

2.1 Preprocessing of Point Clouds

The raw LiDAR point cloud data can include outliers, due to the deformation of several reasons (Wang and Xu, 2017). Most current plane estimation methods are based for least square estimation or their variants. Therefore, outliers and noisy points in point cloud can cause to the false plane orientation (Demir, 2014). Hence, for the first time, filtering outliers and noise techniques applied for the 3D point cloud, based on which the neighbourhood average distance and deviation (Rusu et al., 2008). As a result, only points which supplier the condition for threshold value included for the further analysis (Figure 2).

The proposed method is based on the recognize the vertical planar feature, due to the highways nearby the highway generally created on steep slope faades to stop mass. Accordingly, ground points are not interest on this research and has to be classified. Cloth simulation point cloud ground filtering method have been implemented on the point clouds (Zhang et al., 2016). After the filtering ground points, density based segmentation is possible to recognize vertical plane from intensive data as a line in 2D. It's a way for quick interpretation of the planes instead of analyse dense raw point cloud (Figure 3). Density estimations can be computed by account of the bins rectangular grid area or k-nearest search algorithm. Both of these methods are fast for the density calculations. Precise surface density estimation is done by $density = N/(\pi * R^2)$ formula, here N is neighbour points inside sphere and R is the sphere radius value which is given by user.Further analysis on roughly segmented point cloud need to unravelling for planarity feature to estimate on retaining wall

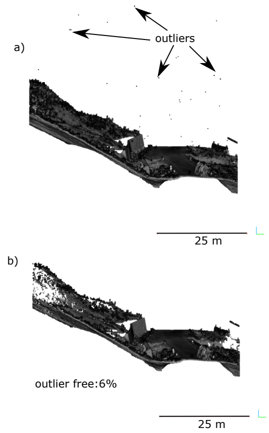

Figure 2. Outliers detection and removal a) raw LiDAR data, b) outliers free point cloud ,removal percentage 6%.

surface. 3D local neighbourhood can be find as k nearest neighbours or in the given spherical radius (Figure 4) (Pauly et al., 2002). Various distance calculation methods can be used here, such as Euclidean, Minkowsky, cosine, Mahalanobis, Cook's and Chi square (Hu et al., 2016). Since the Euclidean distance function is the most widely used in a distance metrics for $k - NN$, we've also used the Euclidean distance metric.

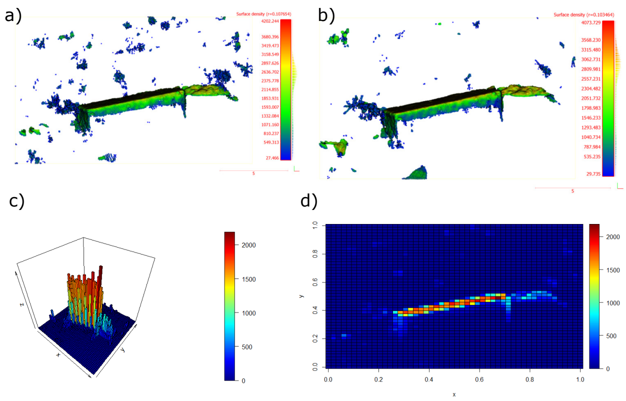

Figure 3. Surface density estimation a) 1^{st} epoch MLS data, b) 2^{nd} epoch MLS data c) 3D histogram plot of density, d) 2D interpreting plot of density with image2D command from R.

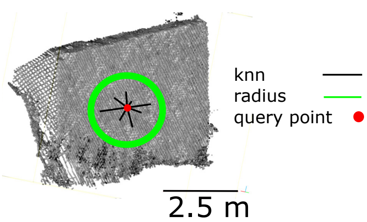

Figure 4. Query point searching algorithms, $k - nn$, radius based.

2.2 Least Square estimation for the best-fitting plane

The least-squares coefficients in multiple linear regression plane are found by solving the algebraic equations for the fallowing intercept d and the slope coefficients or called as normals, a, b, c . The ordinary least square (OLS) in theory is that the height

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component (z) of the point cloud is functionally dependent on the x and y components. The Hessian normal form is considered convenient general form (Equation 1) of plane model (Nurunnabi et al., 2012).

$$ax + by + cz + d = 0 \tag{1}$$

For the most of the situations and complex geospatial data do not fitting perfectly as a planar on point clouds since there is measurement uncertainties in data. Thus total least squares approximation which minimizes the residuals in a direction orthogonal used to the fitting a plane. If the outliers eliminated from point clouds from manually, planes could be recognizable and also least squares estimation should be used for fitting in practice.

2.3 Principal Component Analysis (PCA)

PCA determines the numerous compounds of the variables in spatial data that include the information of geometric shapes, in the sense of irregularity in the data. The hypothesis is that useful information equivalent to the irregularity. In general, PCA is used for data dimensionality minimization and explanation of the high and dense point cloud data. Planarity characteristics depend on the 3D point cloud local neighbours covariance which are provided from the eigenvalues ($\lambda_1, \lambda_2, \lambda_3$) as following equation.

$$P_{planarity} = \frac{\lambda_2 - \lambda_3}{\lambda_1} \tag{2}$$

where λ_1, λ_2 and λ_3 are the eigenvalue of the neighbourhood covarience matrix.

Point cloud as a matrix form (P), the covariance matrix (C) of P can be written as following equation,

$$C(P) = \frac{\Sigma w_i (p_i - \overline{p})^T (p_i - \overline{p})}{\Sigma w_i} \tag{3}$$

where $\overline{p}$, mean of the point cloud x, y, z columns seperately, w_i weights and it is mostly equal to 1.

The obtained eigenvalues which computed from diagonalized matrices, are greater than or equal to zero, $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0$. (Lin et al., 2014)

The mathematics of PCA can be summarized in (Nixon and Aguado, 2012) as the following eight steps :

- Obtain the data P from MLS with coordinate columns
- Compute the covariance matrix C_X.Information about the linear independence between the features
- Obtain the eigenvalues by solving the characteristic equation $det(\lambda_i I - C_X) = 0$
- Obtain the eigenvectors by solving w_i in $(\lambda_i I - C_X) w_i = 0$ for each eigenvalue. Eigenvectors should be normalized and linearly independent
- The transformation is obtained by considering the eigenvectors as their columns
- For classification applications, select and apply planarity function for $\lambda_1, \lambda_2, \lambda_3$ as shown in Equation 2.

While obtaining PCA components, it has been realized that sensitive to outliers, corner points or missing data and density. Therefore, full featured classification of planarity is not possible with only PCA method (Nurunnabi et al., 2012). Thus in this paper, we proposed robust plane regression fitting method to estimate plane normals as in Section 2.4.

R programming language was used for implementation of the PCA due to the high functionality, efficient architecture of R and easy to use its own functions (R Core Team, 2017). The basecore software in R, principal components analysis written as inbuilt function such as, `prcomp`, `princomp` and similarly `eigen` functions.

2.4 Robust Linear Regression Method (PCA-RLM)

Multivariate linear least-squares regression method is sensitive for outliers. In order to remove the outlier effects or to minimize the corruption, several alternative regression methods described in literature (Venables and Ripley, 2002, Cevat and Yetkin, 2006, Gökalp and Boz, 2005). Robust estimation is an alternative approach to local outliers and the heavy-tailed error distributions that tend to generate them. Properly formulated, robust estimators are almost as efficient as least squares when the error distribution is normal and much more efficient when the errors are heavy tailed. Robust estimators hold their efficiency well because they are resistant to outliers. Robust parameters require intense computation time than least squares estimation. However, currently, in this case computing powers have increased effectively. Also, different modern statistical software packages include substantial functionality for robust estimation processing on point clouds (Zeybek and Şanlıoğlu, 2017). Robust regression is implemented by iterating re-weighted least squares (IRLS). `MASS` package from R Programming language has included `rlm` command. There exist on several functions for IRLS applications. We have used bisquare weights from PCA segmented point data (PCA-RLM). The weight function of the bisquare is given as following equation (Equation 4)

$$w_B(e) = \begin{cases} \left[1 - (\frac{e}{k})^2\right]^2 & \text{for} |e| \leq k \\ 0 & \text{for} |e| \geq k \end{cases} \tag{4}$$

Due to the strong weighting (w_B) of bi-square estimator, it has been chosen for large outliers that $k = 4.685\sigma$ value 95% protects the function on behalf of e errors or outliers (Fox, 2002).

2.5 RANSAC

One of the most common methods for estimating a model from 3D point cloud data is the Random SAmple Consensus (RANSAC) (Saval-Calvo et al., 2015). This method and procedure was proposed by (Fischler and Bolles, 1981) and implemented for point sets (Schnabel et al., 2007). The RANSAC algorithm is following two step procedure and progress iteratively through to fit best plane (Li et al., 2016, Tarsha-Kurdi et al., 2007):

- Firstly, minimal point data (for plane it is 3 points) randomly picked out from the point cloud. The plane model can be computed from this sample set. The cardinality of the sample subset is the small-scale adequate to determine the model parameters.

- Secondly, validation for points which have includes plane characteristics of the fitted plane; the distance to the fitting model is computed for designation to the plane model. Outliers has to be disregarded as given error threshold limit from the fitted parameters. These two steps are iteratively continued to the convergence or iteration limit for fitting best plane fit to the data set.

This method is effectively determining the probability based point clouds which presents the function of plane model. However, it depends on the error threshold limits. Thus, we used robust regression models to estimate plane model and compared the results with RANSAC fitted plane.

2.6 Accuracy and Quality Assessment

In theory, the objective of the least square adjustment method is the sum of the squares of the errors times their respective weights minimization for each normal equations (Long Nguyen et al., 2017). Hence, mean error values of each point of planes are computed to explain the differences of the transformation parameters. Mean error (ME) value of each method(RANSAC & PCA-RLM) is calculated by using the following equation:

$$ME = \sum_{i=1}^{n} x_i * a + y_i * b + z_i * c - d \tag{5}$$

where x_i, y_i and z_i are the point coordinates of which belong to the plane
a, b, c and d are the plane normals.

It is important to check the stability of the model fitting parameter estimation using algebraic equations. To achieve this, a best-fit-plane distances were computed for each point distance to the model plane. The distances were derived using the Equation (6) where computed distance determined through the assessment pipeline for comparison plane fitting quality. To arrive at the following expression for the distance from each point from point cloud $P_i = (x_i, y_i, z_i)$ to the plane has been described. The quality of an extracted plane is assessed by the standard deviation.

$$dist = \frac{|ax_i + by_i + cz_i + d|}{\sqrt{a^2 + b^2 + c^2}} \tag{6}$$

2.7 Detection of Deformation

Point cloud comparison for change detection or to recognize displacement can be classified in three groups. These are,

- Cloud-Cloud, point cloud comparison between two different epochs, compare closeness of each point, splitting displacement (x, y, z, components)
- Cloud-Mesh or vice versa, comparison of triangulated mesh through out mesh surface normal to the closest point of second epoch inside point cloud
- Mesh-Mesh, comparison of the closest surface of mesh vertex by TIN surface normal.

Another comparison method is difference of DEM (DoD) analysis which is exclude in this study due to the focus of this comparison method is investigation of vertical plane changing (Figure 5). The main comparison method is discussed here mesh comparisons to detect displacement on fitted different epochs of retaining wall.

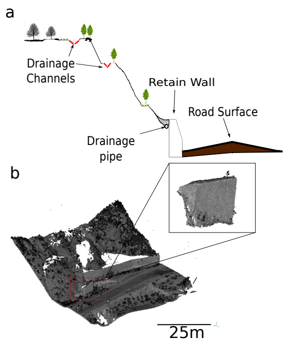

Figure 5. a) Side view of the retain wall design, b) acquired MLS point cloud data and close up to retain wall.

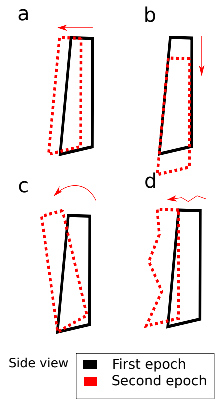

Figure 6. Side view of the wall displacement models, a) horizontal shifting, b) vertical shifting, c) rotational displacement, d) mixed displacement and rotation.

3. EXPERIMENTAL STUDY

3.1 Data Acquisition

Mobile Laser Scanning (MLS) systems provide new, rapid and flexible opportunities in terms of collecting high resolution data and information of the surveying earth. The RIEGL VMX-450 Mobile Laser Scanning System (MLS) has been used with high measurement rates for providing dense, accurate, and excessive feature data at normal traffic driving speeds. MLS 3D data collection, featuring high accuracy and high resolution, provides a basis for a mapping of applications (Figure 5). The surveying of laser observations have remarkable ability to acquisition of vertical retaining walls. The RIEGL software packages were used on data processing. After relative adjustment, the final point cloud accuracy was achieved 0.009 m (east), 0.011 m (north), and 0.025 m (up) (Zeybek, 2017). Matlab (Mathworks, 2015) and R programming packages were used for exported point clouds of retaining wall on further analysis (R Core Team, 2017, Roussel and Auty, 2017).

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3.2 Experimental Results

MLS point cloud data which were inspected from preprocessed used to assess the RANSAC. CloudCompare software was used for RANSAC plane fitting with different point sampling and error threshold (CloudCompare, 2018). Distribution of differences from a plane changes the standard deviations from 0.02 m-0.10 m as error threshold. It's clearly seen that error threshold limits are affected the plane parameters.

The implemented PCA diagonalisation method afore mentioned in Section 2.3. Results are showing the without parameters; planes can be estimated from point cloud only require $k - nn$ value to estimate covariance matrix of neighbourhood. However, it is luck of the estimate curvature limit. For planarity can estimated made by large number of neighbourhood value. On the other hand, this pre-segmentation of point cloud is valuable for robust plane fitting algorithms. The eigenvalues computed from the MLS point cloud data and are analysed for planarity with visually, without quantitative analysis (Figure 7). When RANSAC and PCA-RLM methods were compared, PCA-RLM method was fitted better than RANSAC fitted points. The comparison made from fitted plane distances to the plane for both algorithms (Table 1).

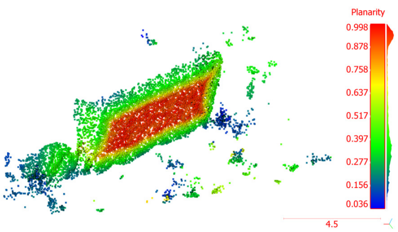

Figure 7. Planarity of PCA analysis.

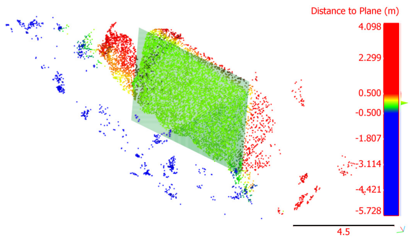

Figure 8. PCA-RLM fitted a plane on retaining wall point clouds.

Method	Max(m)	Min.(m)	Std(m)	Mean(m)
RANSAC	6.089	-6.124	1.484	-0.091
PCA-RLM	4.099	-5.725	1.043	-0.026

Table 1. RANSAC & (PCA-RLM) proposed method descriptive statistics.

Displacements are calculated based on fitted plane inside 5 mm point cloud limited points. In the point cloud which provides the limit count 1902 points were calculated for displacement analysis. Figure 9 shows that the displacement was mostly occurred on North and Up directions. The deformation type of wall displacement interpretation can be clearly made according to the Figure 6. A horizontal (North direction) part of retaining wall have moved forward. Similarly Figure 6b down movements have seen and

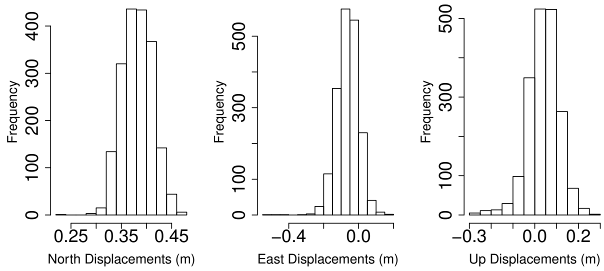

Figure 9. Displacements on North, East and Up axis, respectively

integration with two type of displacements recognized on a retaining wall.

4. CONCLUSIONS AND FUTURE WORK

In this paper, an approach presented for processing of MLS point clouds for retaining wall best fitting plane detection and monitoring. The proposed method has outlined in Section 2 and applied for the single retaining wall. The dataset acquired by RIEGL VMX-450 at Taşkent, Konya, Turkey. The region of interest area has been clipped manually for evaluation. The results of the proposed method stages are demonstrated in Section 3.2. Potential plane features are recognized effectively from the cleared point clouds which do not include large outliers and than planar faces were extracted with first method of RANSAC paradigm. According to the algorithm, given the pre-processing parameters, has detected the plane successfully. However, it can detect multi-planes when the wrong/less point parameters were given. Robust linear regression models which are proposed in this paper estimated the plane without giving any parameters. However, before estimation it requires preprocessing, thus it needs more processing time. The proposed methodology requires optimization for large point clouds. In order to acquire results for fast, high resolution MLS data have been resampled to ten thousand points. It has to be noticed that high capacity workstation computers process less time to process point cloud on parallel architecture. The experiment proves that the proposed method, effectively ability to fit the plane without any pre-parameters and better accuracy than RANSAC (Table 1). However, in order to detect multi-plane retaining wall chains, i.e. threshold each plane point sample further improvements need to be done .

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