LANDSLIDE DETECTION AND ANALYSIS USING 3D POINT CLOUD

Dhivya Harini G (1), Manogari K (1), Monisha A (1), Vani K (1)
[1]Department of Information Science and Technology, College of Engineering, Guindy, Anna University, Chennai, Tamil Nadu, 600025, India.

Email: dhivyayalu@gmail.com; manogarikumaraguru@gmail.com; amonisha98@gmail.com; vanirrk@gmail.com.

1. KEYWORDS: LiDAR, Digital Elevation Model (DEM), DEM of Difference (DoD).

2. ABSTRACT

Natural disasters like landslides cause significant dangers to life, nature and infrastructure in affected areas. So there is a need for an effective monitoring system to reduce the risk of major damages. The major objective is to analyse the deformations caused by landslides and to prevent landslide triggered hazards by using **3D point cloud techniques** on Light Detection and Ranging (LiDAR) dataset. Features extracted like surface roughness are used to classify and assess the damage caused by landslides. The construction of Digital Elevation Model (DEM) with the terrain data before and after the occurrence of landslide helps in determining terrain attributes. The vertical difference in point elevation of the multi-temporal data gives the DEM of Difference (DoD). Performing DoD probabilistic assessment over a terrain matrix of selected window size helps to identify whether the terrain is affected by landslide. With the terrain attributes and probabilistic assessment, the affected region can be classified using K-means clustering. The performance analysis is done by comparing the output of the system with the ground truth data collected from the appropriate dataset. The accuracy of the proposed system is 95% when compared quantitatively in terms of **volume and area of the affected region**.

3. INTRODUCTION

A natural disaster is an adverse event resulting from Earth's natural processes; examples are floods, hurricanes, tornadoes, volcanic eruptions, earth-quakes, landslides, tsunamis, and other geologic processes. Damage property or loss of life, and the severity of economic damage depends on the affected population's ability to recover i.e. resilience and also on the infrastructure available are caused by natural disasters.

3.1 Objective

The objective of the proposed system is to detect and analyse landslides. Also it aims to estimate the amount of damage caused due to the occurrence of landslide. 3D point cloud data helps in quantifying the amount of damage caused.

3.2 Problem Statement

Recent developments in remote sensing have significantly improved the topographic mapping capabilities, resulting in higher spatial resolution and more accurate surface representations. Dense 3D point clouds can be directly obtained by LiDAR or created photogrammetrically, and allow for better exploitation of surface morphology. With the point cloud data landslides can be quantified and analysed.

3.3 Limitations of existing system

Landslide detection deals with mapping areas suspected to mass movement. The existing techniques usually manual techniques are typically field inspection, contour map analysis, aerial photographic inspection etc. However these techniques lacked in accuracy, completeness and reliability required to map small regions with high accuracy. Additionally the existing systems work with 2D images to detect landslides. Due to the lack of depth factor, accurate results are not obtained. Therefore the current methods of assessing and identifying small regions may be inappropriate and difficult to predict.

3.4 Proposed system

To overcome the limitations stated above, 3D point cloud LiDAR technology is used. Modern LiDAR techniques provide the mechanism necessary to map the surface models precisely with high accuracy. It also provides a solution to the challenges faced earlier which includes inaccuracy, vegetation penetration etc. This technology is used to penetrate the dense vegetation and provide efficient results. The main success of this technology is due to the fact that LiDAR data are explicit and are highly automated. Hence 3D point cloud LiDAR technology is used here to detect and classify landslides.

4. SYSTEM ARCHITECTURE

In this study we implement the method of using multi-temporal LiDAR data (Time series of LiDAR data) to detect the landslides using 3D Point cloud. The overall system architecture of the proposed system is described in Figure 4.1.

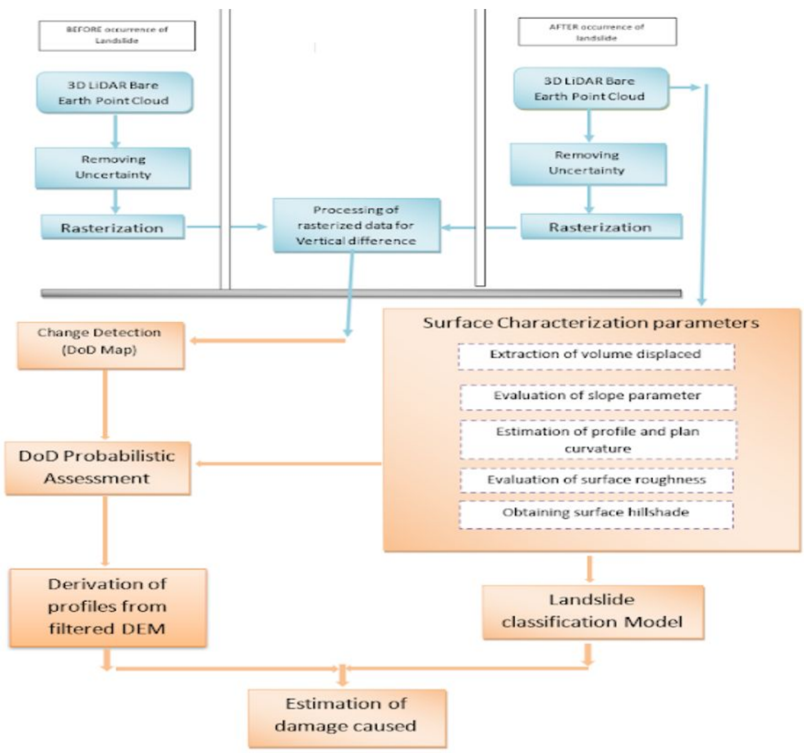

Figure 4.1: System Architecture

4.1 Removing Uncertainty

One important factor is characterizing uncertainty found in the data that helps to determine real surface deformation from changes that may be due to other factors, like noise, errors. It is necessary to evaluate the uncertainties found in data sources in order to perform change detection with high confidence. The calculation of DEM uncertainties incorporates a minimum level of detection (min-LoD) threshold to distinguish real surface deformation from noise. Observed elevation changes below the calculated threshold are typically ignored and those above the calculated threshold are treated as real.

4.2 Rasterization

Raster or gridded data are rendered on a map as pixels which are stored as a grid of values. Each pixel value represents a point on the Earth's surface. A raster file is a composed of same size regular grid of cells. LiDAR is an active remote sensing system that records reflected or returned light energy. Records of the strongest reflections of light as discrete or individual points are returned by discrete LiDAR system. X, Y and Z value associated with each point in the LiDAR data. The amount of reflected light energy that is returned to the sensor is represented as intensity. Rasterization is creating the DEM (Digital Elevation Model) for both before and after occurrence of landslide with 3d point cloud data of bare earth.

4.3 Change Detection Map

The change detection for occurrence of landslide comprises of DoD mapping and probabilistic change detection. DoD is DEM (digital elevation model) of Difference. The difference in surface elevations from digital elevation models (DEMs) derived from repeat topographic surveys gives the volumetric change. To perform DoD accurately, the registration and acquisition of the data be prepared consistently between dates (as in the C2C approach). The 1D elevation changes are obtained by DEM subtraction with cell-by-cell approach.

4.4 DOD Probabilistic Assessment

Surface changes are vital to detect, but calculating the probability of the change detected being real or not is as equally important. The higher the probability, the higher the chance of the change detected being a real surface deformation. This helps in filtering the lower probability changes. A probabilistic signed rank test is proposed to map the local neighborhoods of vertical differences. The signed rank test evaluates the null hypothesis (H0: 0/ ≥ M) that the observations in the local neighborhood come from a continuous distribution with a median greater than M where 0/ is the treatment effect i.e. vertical changes as given by following hypothesis.

$$H0: 0/ \geq M \text{ vs. } H1: 0/ \leq M$$

4.5 Surface Characterisation Parameters

Landslides are described using the geo-morphologic features, and, in general, various numbers derived from surface models parameterized land formations. Depending on landslide shapes and types, the distribution of the above mentioned parameters may show correlation with the landslide areas.

4.5.1 Aspect:

The slope orientation of each point or cell in the DEM, the compass direction that a land surface faces is called aspect. It is expressed as an angle and calculated with the Equation 4.1.

$$\theta = \mathit{arctan}(\ nx/ny\ ) \tag{4.1}$$

4.5.2 Curvature:

The second derivative of the surface in general gives the curvature. Profile curvature is defined as the curvature along the steepest downward gradient. The plan curvature is the curvature perpendicular to the downward gradient. The profile curvature is measured in the direction that is determined by the parameter aspect.

4.5.3 Slope:

The steepest downward gradient of the surface at any point gives the slope parameter. Using Equation 4.2 slope of the region is estimated.

$$SD_8 = \max_{i=1\text{-}8}[Z_9\text{-}Z_i\ /\ h\Phi(i)] \tag{4.2}$$

4.5.4 Hillshade:

The relief is powerfully represented by hillshading. A shaded relief for a digital elevation model is given by hillshade based on the angle between the incoming light beam and the surface that can be evaluated using Equation 5.1 and Equation 5.2.

4.5.5 Roughness:

The deviations of a surface are quantified by a metric called roughness that is calculated using Equation 4.3. The maximum difference between any two points in a surface patch gives roughness of that region. Roughness is the largest inter- cell difference between the central pixel and its surrounding cells in DEM representation.

$$R = \max_{i=1\text{-}8}[Z_i\text{-}Z_9] \tag{4.3}$$

4.5.6 Volume:

Volume is the estimated amount of soil displaced due to the occurrence of landslide. Volume is estimated by aggregating the volume of vertical differences. Volume is the product of area corresponding to a point and it's vertical difference.

4.6 Derivation of profiles from filtered DEM

The probability map generated using the signed rank test displays various magnitudes and locations of probable topographic change but not the exact regions. To map on to the regions a filter is formulated with the characterisation parameters - slope, roughness, curvature and hillshade and Wilcoxon's signed rank test contributes to map on to the landslide affected region. The filter is multiplied element-wise with the Digital Elevation Model to map on the landslide affected zone on the dataset surface.

4.7 Landslide Classification Module

Classification is done to ensure that a particular type of deformations comes under one single category. K-Means clustering algorithm is a popular clustering algorithm. The clusters generated from the K-means model is then given a class label with respect to the DoD value and average of roughness value from the clusters in an increasing order i.e the one with the least average roughness is labeled as Not affected region.

4.7.1 K-Means clustering:

K-Means clustering algorithm attempts to split the given dataset into k number of clusters which in this case is 4 that is Not affected region, Least affected, Moderately affected and Highly affected region. Initially 4 centroids are chosen randomly so that all of them are unique. A centroid is a data point at the center of the cluster. These centroids are then used to train the KNN classifier.

4.8 Estimation of Damage Caused

The amount of damage caused in terms of affected area and affected volume is the output of this module. The Wilcoxon's signed rank test method is used here.

4.8.1 Wilcoxon's Signed Rank Test:

A probabilistic signed rank test is proposed to evaluate local neighborhoods of vertical differences. The non-parametric signed rank test developed by Wilcoxon makes no assumption about the underlying distribution, thus making our predictions more robust in the form that the distribution is not dependent on any parent distribution nor on its parameters. The signed rank test evaluates the null hypothesis (HΘ: q ¿= M) that the observations in the local neighborhood (w w cells for the DoD approach and nearest neighbors for the C2C approach) come from a continuous distribution with a median greater than M (Hollander and Wolfe), where q is the treatment effect.

4.8.2 Affected Area:

The area corresponding to a single point can be derived from the number of points in 1 m2 area. With this the total area is computed by multiplying the number of points with the area of a single point.

4.8.3 Affected Volume:

Affected volume is the estimated amount of soil displaced due to the occurrence of landslide. The DoD and the classified output's area are used to calculate the volume of soil displaced. The DoD gives the vertical difference between the DEM. Volume is estimated by aggregating the volume of vertical differences. The area corresponding to a single point is multiplied with the vertical difference value to get the total displaced volume.

5. IMPLEMENTATION OF WORK

The proposed system analyses the LiDAR data of bare earth surface before and after landslide and constructs the rasterised DEM from the las files.

5.1 Collection Of Dataset

The LiDAR data used for landslide analysis was collected by National Center for Airborne Laser Mapping. The data was collected from Slumgullion Landslide, Colorado before the occurrence of landslide on July 3, 2015 and after the landslide on July 10, 2015.

5.2 Data Preprocessing

The data file is checked for laz compressed file and converted to las file format.the x, y and z point data of the records is read and stored in the object. The point data is then normalized by multiplying with scale factor and adding the corresponding offset. From the point data extracted from las file, a PLY (Polygon File Format or the Stanford Triangle Format) file is constructed.

5.3 Digital Elevation Model

DEM is used to refer to any digital representation of a topographic surface.Construction of DEM takes x,y,z points as its input and generates the digital model. A linespace is created for x and y coordinates. With the linespace, a mesh grid of x and y is generated. The vertical component (z coordinates) is obtained by cubic interpolation of the point cloud data. The z value is normalised using CMAP. It is the converted to RGB colour format. Then the RGB colour intensity with contour lines are plotted into an image for the x and y coordinates.

5.4 Change Detection (DOD) MAP

The point data is converted into a matrix with x coordinate as row values, y coordinate as column value and z point values as the array values for the data both before and after landslide. The x and y common range for both the matrices is found and a new matrix is defined for vertical difference. The difference in vertical component (z value) is calculated and stored in this matrix. This process is repeated for each and every voxel. A DEM for this computed matrix is generated and this is called DoD which is also known as vertical difference.

5.5 Surface Characterization Parameters

The parameters are computed for every surface point from the collected data set and these parameters help in the classification of landslide. The parameters show correlation between values depending on the type of landslide occurred. It is proved that landslide with high affected region has a huge roughness value compared to less affected landslides. Slope, roughness, curvature and hillshade of the terrain are estimated.

5.6 DOD Probabilistic Assessment

Probabilistic signed rank test is proposed to evaluate the local neighborhood of landslide. This non-parametric method of probabilistic assessment is proposed by Wilcoxon hence called Wilcoxon’s signed rank test. This method is used due to it’s high robustness and no assumption about the distribution of the dataset or correlation in between it. The DoD matrix is parsed with a 3X3 sliding window. 3X3 is the appropriate size of a sliding window and making 5X5 or of higher dimension will reduce the accuracy of the result obtained due to the distance increased from the center. The null hypothesis assumed is that the landslide has occured in the current window.

5.7 Landslide Classification

The dataset is fed as input to the K-means clustering model. The clustering model works on the principle of Euclidean distance. DoD value and the roughness values are used for the classification.

5.8 Estimation of Damage Caused

The predictions of Landslide classification and DOD probabilistic assessment are used to map to the landslide profile and estimate the area and volume of the affected region.

5.8.1 Area of Damage: With the meta data of the dataset collected, the area of a single point is computed. The total area of the affected region is estimated with the single point mapping.

5.8.2 Volume of Damage: Volume of identified profile is estimated by aggregating the volume of vertical differences. The area corresponding to a single point and hence the total area is computed previously. This data is multiplied with the vertical difference value to compute the volume.

6. RESULTS AND PERFORMANCE ANALYSIS

6.1 Results

Multi-temporal LiDAR data of affected region in Slumgullion is analysed with elevated models and the following results were inferred.

6.1.1 Elevation Models: Visualizing 3D point cloud data gives better understanding of the data. The DEM of multi-temporal data is shown in Figure 6.1.

a) b)

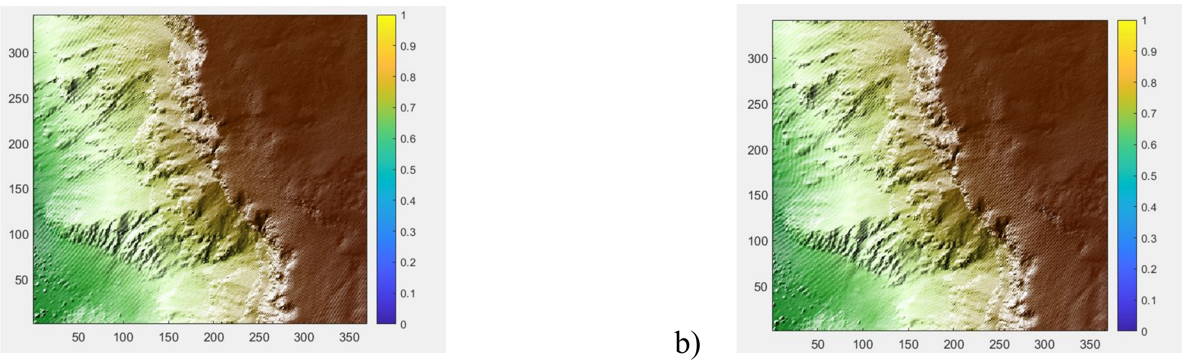

Figure 6.1: DEM of terrain before (a) and after (b) landslide

6.1.2 Difference of DEM: From the multi-temporal DEM of terrain both before and after the landslide, difference of DEM is constructed which can be further used to analyse the damages caused by landslide. The elevated model of vertical difference from multi-temporal data is shown in Figure 6.2.

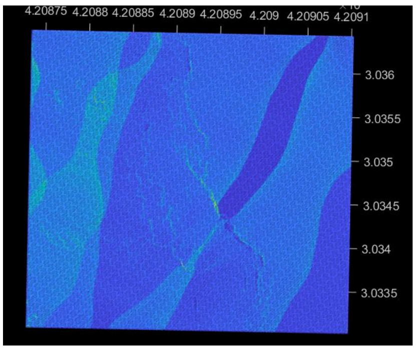

Figure 6.2: DoD of affected region

6.1.3 Derivation Profiles from Filtered DEM: It is observed that higher the vertical change within the local neighborhoods and the propagated uncertainties, the higher the probability that the change is real. In the figure 6.3. the Brown represents the landslide affected region and the blue represents the normal region.

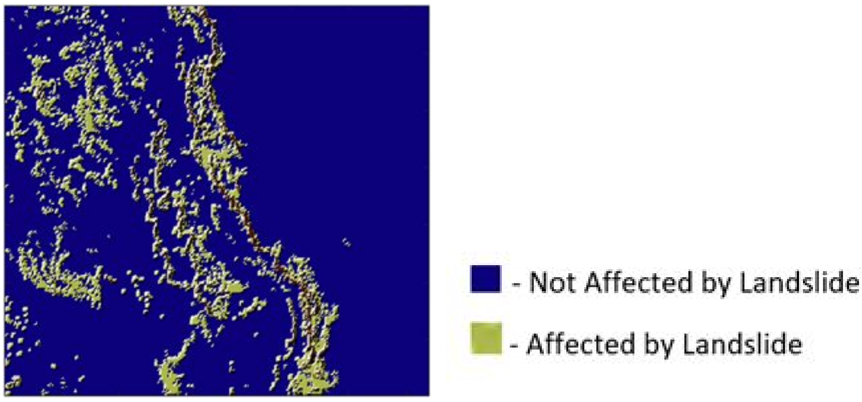

Figure 6.3: Mapped Profile of affected region of the surface

6.1.4 Classification of Landslides: The classified terrain output is shown in Figure 6.4.

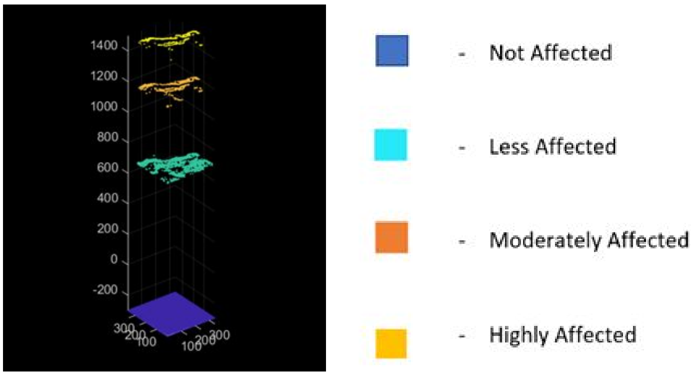

Figure 6.4:Classified output

6.1.5 Estimated Amount of Damage: Estimation of the damage caused helps in quantizing the damage in terms of area and volume.

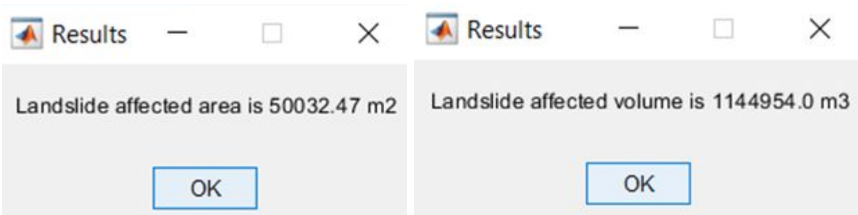

Figure 6.5: Damage caused - Area and Volume

6.2 Performance analysis

Performance analysis is carried out to estimate the accuracy of results. For the analysed region the results of the system are compared with the ground truth table of the same region to show the accuracy. The accuracy total area and the volume of sand displaced has been computed. The overall performance is calculated by the equation 6.1.

$$\text{Accuracy percentage} = (\text{Computed Value} / \text{Actual Value}) \times 100 \tag{6.1}$$

Figure 5.1 consists of the ground truth of the Slumgullion Landslide occurred on 3rd to 10th July, 2015.

Feature	Dimensions of the inactive landslide	Dimensions of the active landslide
Area of deposit *	4.74 km^2	1.46 km^2
Length	6.8 km	3.9 km
Width		
- head	1,130 m	280 m
- narrowest part	290 m	150 m
- toe	530 m	430 m
Relief		
- elevation of top	3,700 m	3,500 m
- elevation of tip	2,700 m	2,960 m
Average slope		
- deposit only	7° (12%)	----
- including main scarp	8° (14%)	11° (19%)
Thickness		
- average	40 m	13 m
- average on thalweg of buried valley	90-100 m	---
- maximum	140 m	48 m
Volume		
- earth flow deposit	168 x 10^6 m^3	19.5 x 10^6 m^3
- detached mass **	142 x 10^6 m^3	----
Length : width	> 6:1	9:1

Figure 6.6 Ground truth values

From the Figure 6.6, the total volume and the total area calculated by adding all the values together(both active and inactive) from the ground truth value.

Total Volume = 329.5 x 106 m^3

Total Area = 6200000 m^2

The Figure 6.7, consists of the area and volume values computed for each and every sub-region by the proposed system and hence the overall total.

System Ouput		
Points	Area in m^2	Volume in m^3
1	339721	21150878
2	255181	13878235
3	366347	19096462
4	242651	14600571
5	330022	30236790
6	374912	33434772
7	302983	19039588
8	239803	14834168
9	280232	15185431
10	345602	22160893
11	244658	17901549
12	449431	19564254
13	354834	16223768
14	281665	12397118
15	364854	14029143
16	411772	17287390
17	246113	7559076
18	372191	10704263

Figure 6.7 calculated area and volume

Total volume = 319.28 x 106 m^3

Total Area = 5802922 m^2

6.2.1 Performance in terms of Area

The computed value of the area is 5802922 m^2. The ground truth value of the area is 6200000 m2. Hence the accuracy percentage is given in the 6.2.

Accuracy percentage = (5802922 / 6200000) x 100 = 93.5% (6.2)

6.2.2 Performance in terms of Volume

The computed value of Volume is 319.28 x 106 m^3. The ground truth value of the Volume is 329.5 x 106 m^3. Hence the accuracy percentage is given in the equation 6.3.

$$\text{Accuracy percentage} = (319.28\text{x}10^6 / 329{:}5\text{x}10^6 \text{ x}100) = 96.89\% \quad (6.3)$$

7. CONCLUSION

Processing 3D point cloud data will help in quantifying the amount of damage caused due to landslide. The regions affected due to landslide have been analysed and the amount of damage caused has been estimated. The various features such as slope, area, volume, hillshade, curvatures have been extracted and analysed. The most affected region has been identified and monitored. We have classified the affected region into most affected, moderately affected and least affected regions. Performance analysis has been carried out successfully by using the ground truth of Slumgullion Landslide.

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