GEOMETRIC FEATURES INTERPRETATION OF PHOTOGRAMMETRIC POINT CLOUD FROM UNMANNED AERIAL VEHICLE

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ABSTRACT:

Recent days point clouds have become one of the most common 3D sources of information which is provides accurate geometry features of the object. 3D point clouds can be derived from either photogrammetry, Lidar or SAR in some cases depending upon the application. These point clouds consisting of 3D geospatial location of an object in form of XYZ coordinates which can be used in various ways to deduct information related to that object either based on visualisation or geometrical interpretation. Quality assessment standards for these point clouds are still very much in nascent stage with optimum accuracy in relative terms only. In this paper, multiple scale of point cloud has been used to understand the level of information these clouds consist on these multiple scales. Based on the 3D spatial information of these point cloud in local neighbourhood, some of invariant geometric properties can be computed for each 3D point with respective covariance matrix. These can be used to describe the local 3D structure using eigenvalues for these matrices. Using these Geometric features an approach is developed to understand the point cloud quality assessment. The proposed methodology exploits these special geometric properties to evaluate the 3D scene structure. Further, the point cloud is classified using shape detection algorithm which evaluates the geometric features to detect the mathematical shapes in the point cloud. This paper also enlightens on different geometric features that can be extracted from a point cloud and the importance of it.

1. INTRODUCTION

1.1 Background

In recent times, point clouds and 3D data acquired from different techniques such as; Photogrammetry, Computer vision and Lidar have become one of the most revolutionised field in the geospatial domain. The information acquired using these techniques opens up a broad new prospect for researchers to advent applications in 3D modelling, scene understanding, classification and various other domains. From a technical perspective, scanners and cameras are line-of-sight sensors, hence point clouds obtained from these techniques inherently suffer from occlusions and incomplete data and exhibit extreme variations in point density (depending on the distance to the sensor and the surface orientation). Both effects are a lot stronger outdoors, where they are not mitigated by the limited size and constrained shape of rooms (Hackel et. al. 2016). 3D scene understanding using point cloud data structure is very complex in nature as regularity in the data information is missing. While geometric features computed over those point cloud could be used to derivative components on the basis of eigenvalues. Which can be utilised as a great tool to extract a better set of parameters to improve the scene understanding using point cloud data.

Point cloud generated from photogrammetric computer vision has mostly been used in this research. Point cloud are quite extensive both in volume and structural sense, as it store unstructured discrete points with uneven density and sometimes redundant data when acquired from multiple sources. Assessing the quality of such data is very cumbersome and separating the inliers from outliers is one of the most tiresome job when doing manually. In this study, we propose a workflow by extracting or we can say computing geometric features of a point cloud on multiple scale to derive a range of threshold which can give us some quality check parameters for a point cloud. Using complex model for learning contextual relationship is quite extensive, so our focus is to use of some versatile features to provide a higher interpretability of point cloud-based 3D geometric features and to understand the shape detection algorithm execution on point cloud dataset.

1.2 Related works

In the following section, we briefly summarize related work and thereby address a typical processing pipeline for generating point cloud from Unmanned Aerial Vehicle (UAV) photogrammetry, extending those point clouds for geometric feature extraction and then utilising these geometric features for various mathematical shape detection.

A. UAV Photogrammetry

UAV are low-cost method for surveying and data acquisition. Photogrammetric principles for generating 3D scene is based on the principles of binocular vision, space resection, relative orientation and absolute orientation, in which geometric relation between stereo images and the absolute transformation of coordinate systems are utilised (Zhang & Yao, 2008). A common object is visualised from two perspective positions to extract the 3D poses of an object in a virtual environment. A conventional photogrammetric workflow starts with the acquisition of images with certain pre-defined rules. These rules are very important for a successful photogrammetric project, i.e. enough overlaps between images (Bedford, 2017), configuration of image network (Murtiyoso et. al. 2018), photographic quality. Determination of Ground Sampling Distance (GSD) and distribution of Ground Control Points (GCPs) hold the same importance in generating good results from photogrammetric process as predefined set of rules. With recent advancement of UAV and drone based data acquisition techniques, photogrammetry has now become very accessible to research personals and surveyors. The opportunities provided in the field

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of geospatial science is diverse. Some bottleneck still exists in UAV photogrammetry as compared with the conventional photogrammetric aspects (Jain, 2021).

B. Geometric Feature Extraction

Geometric features are tools which assess the point cloud based statistics by extracting Eigen vectors with attached Eigen values from the data using Principle Component Analysis (PCA). Eigen vectors and Eigen values gives some idea about the local shape of the point cloud when combined with some of the other input parameters such as radius of the neighbourhood, density and scale (Bazazian et al., 2015). They provide some of the great statistical information such as Normal change direction, Curvature, Eigentropy, Planarity, Surface variation, surface roughness, Sphericity, Verticality, First order moment, Surface density, Volume Density and many more. These tools are very useful for extracting information such as contours (Hackel et al., 2016a), edges (Bazazian et al., 2015), 3D line segment (Lu et al., 2019) and contribution of each normal vector in different axis i.e., x, y and z (Kushwaha et al., 2019) from an unstructured point cloud data. A detailed address regarding elements like point sampling, neighbourhood recovery, feature extraction and feature relevance assessment is presented in (Weinmann et al., 2017).

C. Shape Detection

Jorgensen has presented how supervised learning techniques can be used to an existing shape description in terms of local feature descriptors (Jørgensen et al., 2015). RANSAC shape detection algorithm is an efficient tool to extract different geometrical shapes from the point cloud (Schnabel et al., 2007). Which is also implemented in this study. Using RANSAC and PCA together has allowed fast matching without normal estimation and segmentation. As the radius computed by the sphere using RANSAC is used as the radius of cylinder and the straight and curvature is extracted from PCA (Jin & Lee, 2019). Some of the mathematical models that can be extracted from the point clouds are Sphere, Cylinder, plane, etc.

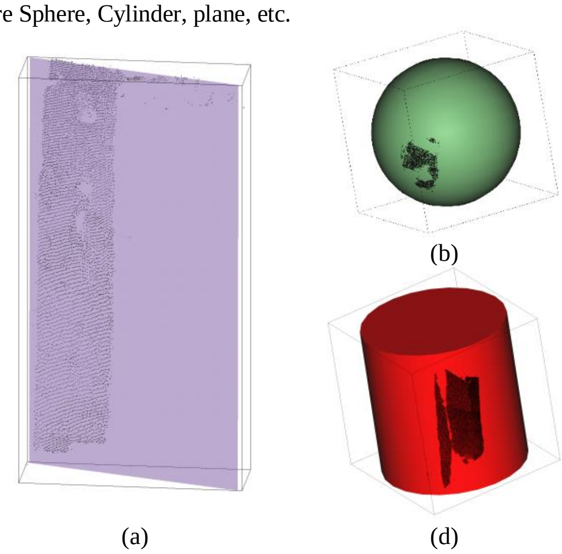

Figure 1. Shapes detected with the points detected for a) Plane, b) Sphere, c) Cylinder

1.3 Structure of paper

Paper is structured in very crisp manner as to provide maximum impact in optimised way. Section 2, provides the description regarding data used and methodology followed for computation and assessment. Section 3, provides the discussion over the result generated and section 4, concludes the overall research components and analysis.

2. DATASET USED AND METHODOLOGY

2.1 Data Used

In this study, a hilltop fort located on Madan Mahal hill, in Jabalpur, Madhya Pradesh, India has been surveyed photogrammetrically using UAV based images. Data acquisition was done with the oblique camera configuration and in a circular pattern as shown in Figure 2, so that the main focus of the camera sensor during the data acquisition is on the structure of study.

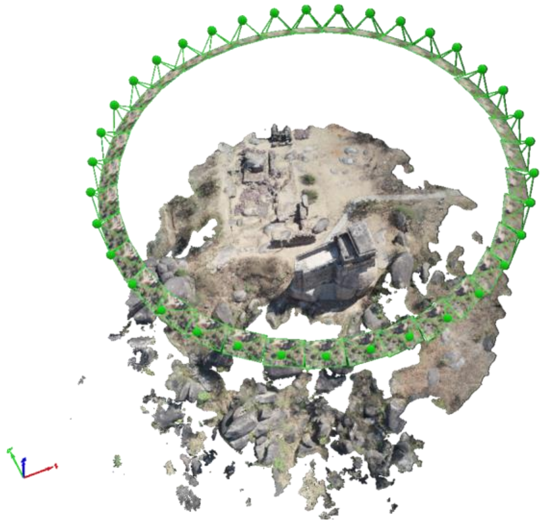

Figure 2. Photogrammetric point cloud data with UAV image acquisition positions

2.2 Methodology

Images acquired from the UAV were processed using Pix4D Mapper pro software for dense 3D point cloud generation. Initially, Images were aligned to with reference with other. Key features were detected and extracted, then features were matched for 3D scene reconstruction. 3D mesh model is also created for understanding the 3D geometry of the structure in detail which is shown in Figure 3.

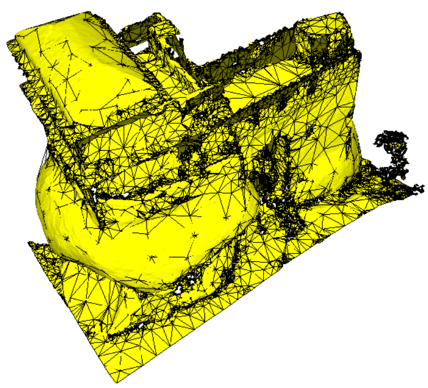

Figure 3. 3D Mesh of the hill top fort generated using CGAL

The generated point cloud is further used in assessment of geometric features extracted from this point cloud based on PCA in open-source platform CloudCompare. For extracting geometric properties based on point cloud information, we have

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used cloud compare based toolbox. Cloud Compare is an open source project which is very robust for comparing and doing multiple analysis over point clouds, mesh and other 3D data structures. We have used some but not all of the features to check the quality of our point cloud, and for multiple neighbourhood scales. The detailed methodology is represented as a workflow in Figure 4 below.

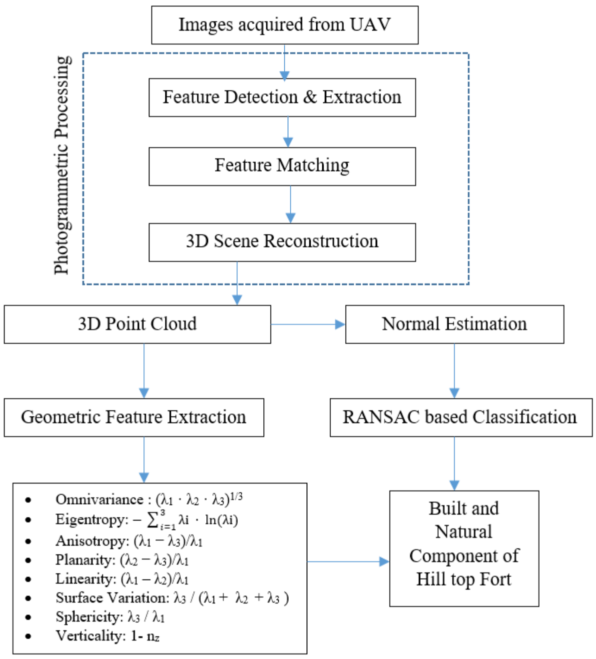

Figure 4. Overview on the proposed methodology

2.2.1 Computing Geometric Features from point clouds

In cloud compare we can calculate various geometric features such as anisotropy, Eigentropy, Planarity, Surface variation, surface roughness, Sphericity, Verticality etc. these geometric features are mostly computed using the PCA. In which the whole data structure set is used to extract the direction or gradient information in which the maximum number of data points lies. Eigen vectors and Eigen values summarises the gradient information related to the dataset such as Eigen vectors shows the direction of those gradients while Eigen values provides the strength of the gradient in a particular direction.

For getting a precise result, in computing geometric features some of the important things which we have to keep in mind are:
a) The right radius of neighbourhood,
b) The scale of objects or structures under consideration,
c) The units in which the point coordinates are expressed (Local, or global),
d) The density of the point cloud data used as well.

Eigen Vectors play a vital role in the whole analysis of geometric feature extraction of point clouds. One of the parameters, radius of the neighbourhood is used in extracting results apart from them scale of the object under observation, the unit in which the point coordinates are expressed, and the density of the point cloud as well are considered before executing this analysis. The eigenvalues λ_1, λ_2 and λ_3 of structural tensor with $\lambda_1 > \lambda_2 > \lambda_3 > 0$ can be directly used to describe the local 3D structure (Weinmann et al., 2013, 2017). These features are based on the Eigen values of the covariance matrix of a local neighbourhood. They also include moments around the corresponding eigenvectors, as well as features computed in vertical columns around the point (Hackel et al., 2016b).

The covariance is a measure of how much each of the dimension diverges from the mean with respect to each other, the Eigen values of the covariance matrix measure the change of the corresponding point near the direction of the Eigen vectors (Bazazian et al., 2015). Thus, the largest and smallest Eigen values of the covariance matrix are associated with magnitude with strong and very small interactions (Garland, 1999). There are three Eigen values of the covariance matrix of three-dimensional datasets, and the Eigen vector of the smallest Eigen values is associated with a normal vector. Thus, in a flat area, the number of very small eigenvalues will be zero and if any bends or curvature are present in the area defined by the neighbour of the sample point, the number of small eigenvalues will be large.

The surface variation for each sample point with a neighbourhood allows us to distinguish whether the point belongs to a flat plane or to a salient point (Edge) in the point cloud. Since the smallest eigenvalue of covariance matrix for the flat surface is zero, then the value of the surface variation for the flat surface would be zero.

Computation of normal of a surface is one of the most inconsequential in point clouds. As for the point cloud, they are an estimation of physical surfaces, so calculating these features is not direct. Either a least square approach should be taken, or a point cloud derived mesh can be used as reference to determine the orientation of each neighbourhood. The computation of normals has been done using robust version of Randomized Hough transform as mentioned in (Boulch & Marlet, 2012).

3. RESULTS AND DISCUSSIONS

Geometric features are demonstrated in form of coloured point cloud with reference histogram plot for the values extracted from the analysis of Eigen values. They are discussed in pairs as they have some correlation in between, For eg: 1) Roughness and PCA, 2) Planarity and Verticality, 3) Surface density and Omnivariance.

Figure 5. Hill top Fort point cloud

These point clouds in raw form mostly represent the geometric aspects of the object in question. Semantic information

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enrichment can be done either by performing point cloud classification as post processing of point cloud generation or segmenting data with similar attributes such as, surface normal or curvature statistics. For that matter, these geometric features could help in deriving general solutions rather than unique solution with respect to the data specific characteristics.

Figure 6, shows the result for roughness and PCA parameters for the point cloud data. It can be visualised with reference to the histogram that the more the roughness and PCA are somewhat reciprocal to each other. Roughness is derived for the lowest eigenvalue with respect to sum of eigenvalues for all the dimensions in the point cloud data. While PCA is straight forward principal component analysis carried over in the direction of the second largest Eigen vector. Both the parameters are computed with a neighbourhood radius of 0.5.

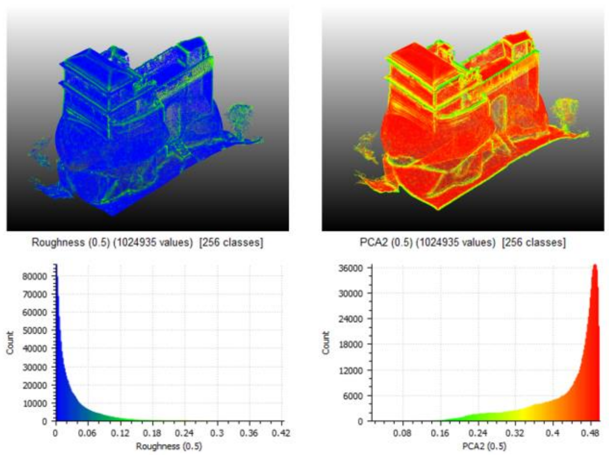

Figure 6. Extracted Roughness and PCA from point cloud

The verticality is well-suited for distinguishing between facade and horizontal planes, and planarity does the opposite (Figure 7). As per equation, showed in the workflow above planarity is related with eigenvalues while in case of vertically it is extracted using normal z component from each 3D point. The smoothness of the surface which is somewhat related to roughness measure can be describe by planarity and the quality of plane fitting for normal vector estimation as well.

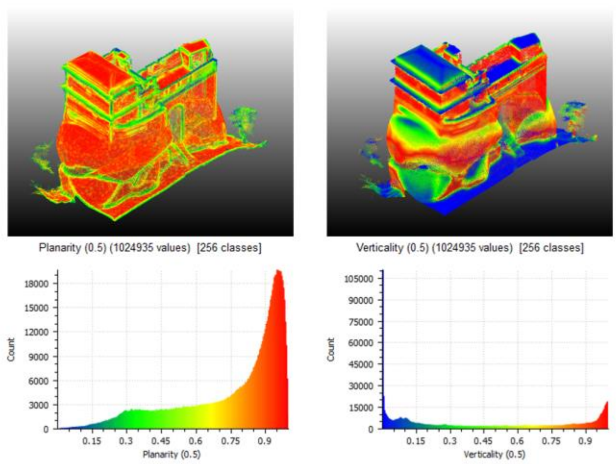

Figure 7. Extracted Planarity and Verticality from point cloud

Omnivariance in case of point cloud is based on three eigenvalues $\lambda_1 > \lambda_2 > \lambda_3 > 0$, and describes how a neighbourhood of points spread non-uniformly across a 3D volume (Waldhauser et al., 2014). While Surface density provides a relationship between the number of neighbours with respect to its neighbourhood surface ($N / (\pi R^2)$) or in case of volume with respect to neighbourhood volume ($N / (4/3*\pi R^3)$).

After extracting these features, it is important to remember that some of them may include redundancy in information for the classification process. Although many classifiers are thought to be indifferent to the existing dimensionality in principle, their performance has been shown to be influenced by such redundant or unnecessary information. As a result, selecting a compact subset of the most relevant features that allows classification without significant loss of predictive information is frequently preferred. To overcome the curse of dimensionality, with improved class separability, and for facilitating interpretability, such feature selection is critical (Weinmann et al., 2013).

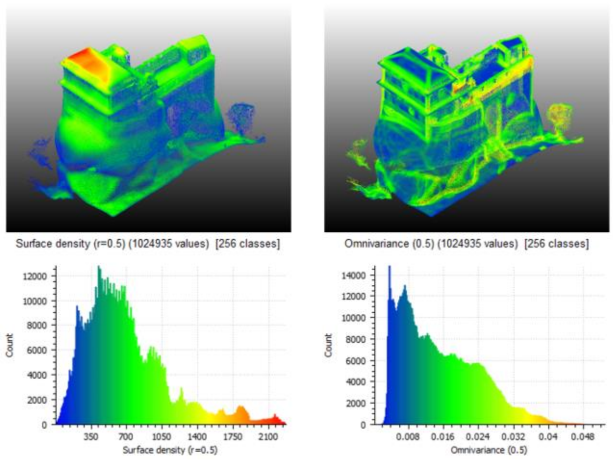

Figure 8. Extracted Surface Density and Omnivariance from point cloud

Sometimes a single neighbourhood is unable to describe the local 3D structure at different scales and thus in such cases we have to use multiple neighbourhoods to understand how the local 3D structure behave across different scales. Low-level geometric features reveal a different structural behaviour for different neighbourhood. A visualisation of the different geometric properties with respect to varied neighbourhood radius is provided in Figure 9 (Triangle and star mark represent near and far points from seed point respectively in 3d point cloud) and Figure 10 with their occurrences. Multi-scale assessment suggests the invariability in components of geometric features derived from the above-mentioned workflow. The neighbourhood sizes used to calculate statistics are chosen by the user and should ideally be based on knowledge of the typical sizes of the objects of interest. Larger scales show macro-trends like the shape of items up to several metres in size, while smaller scales capture the details of objects that would be lost in larger scales, such as objects of a few centimetres in size.

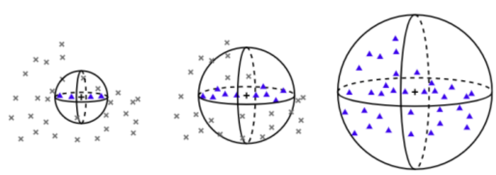

Figure 9. Neighborhood ball at different scale (Brodu and Lague, 2012)

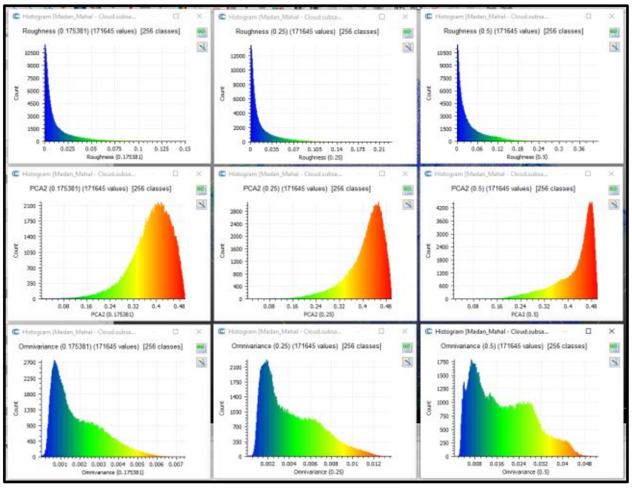

Figure 10. Multi-scale assessment of Geometric features

3.1 Experimental results

We experimented over the data for extracting built and natural component from the point cloud data shown in Figure 5. The natural Rock boulder of Granite had been utilized as one of the wall of fort. The natural rock boulders of Granites on Hill Top were utilized in the fortification as protective wall of Fort. Considering the rock boulder height the side walls and roof had been constructed with a Low lintel level in the second storey. The fort lies in the isolated hillock at a height of 500m above Mean Sea Level (MSL) on the Madan Mahal Hill (Diwan et. al. 2020).

In this study, Random Sample Consensus (RANSAC) shape detection tool in cloudcompare is used to detect the planes, spheres and cylinders RANSAC algorithm does the iterative computation to estimate the mathematical models from a set of dataset. When this tool was executed we got 50 planes, 35 cylinders and 12 spheres from the overall point cloud. Then these classes were used to segregate between built and natural component from the overall point cloud dataset. The classified point cloud dataset is shown in Figure 10.

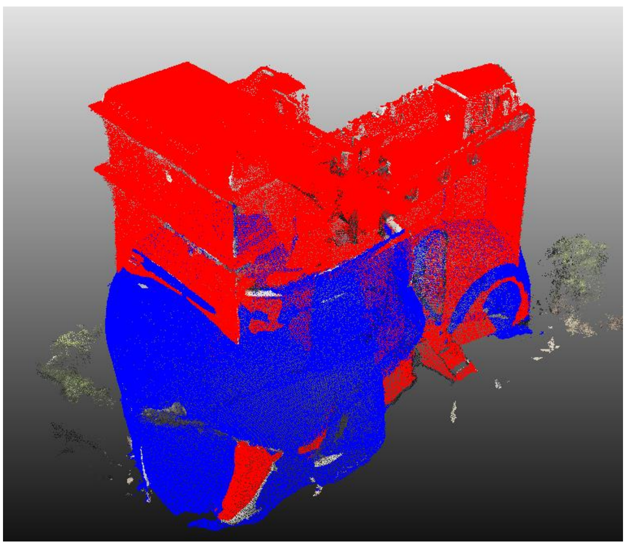

Figure 10. Classified point cloud Built (red), Natural (blue)

Figure 11. Classified Built and Natural components of Fort point cloud a) Left side Elevation, b) Right side Elevation

The blue represents the points corresponding to natural component and red represents the built component of the structure. Further the results are shown in comparison with the actual point cloud side by side in Figure 11. The RANSAC shape detection can further be improved by changing the parameters for shape detection. Cloudcompare has different set of parameters like max distance to primitive, sampling resolution, max normal deviation, overlooking probability and some advance parameters.

4. CONCLUSIONS AND FUTURE SCOPE

Geometric features extracted from point clouds are one of the intricate tools which can be further utilise to enhance the classification and segmentation problems. Point cloud being an unstructured data can be very problematic for performing operations such as object detection and feature extraction, using theses derived information (such as: planarity, verticality, Omnivariance, roughness etc.) can help us to better understand the quality of datasets. In this study, we have demonstrated these Eigen value based analysis using an open source platform over a photogrammetric point cloud using PCA. These feature classes could be very useful in designing more robust ML or DL algorithms using the existing information extracted from the point cloud. An experiment has been performed over a Hill-top fort point cloud to create multiple geometric features and a binary class of built up surface and natural surface component. We also provided an understanding of these features from a mathematical standpoint. Somewhat quality of a datasets can be judged from these tools for minimising the error in later processing and 3d modelling stages.

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