UAS-Based LiDAR Mapping

Video F-II



Local Point Density Estimation



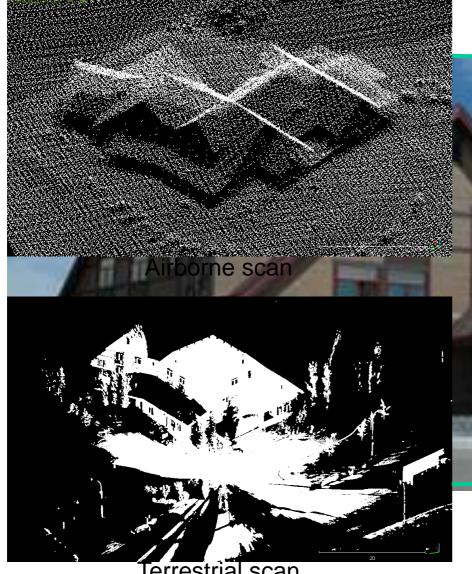
Overview

LiDAR Data Characterization

- Local Point Density (LPD) Estimation
- Local neighborhood classification



LiDAR Mapping: Ultimate Goal



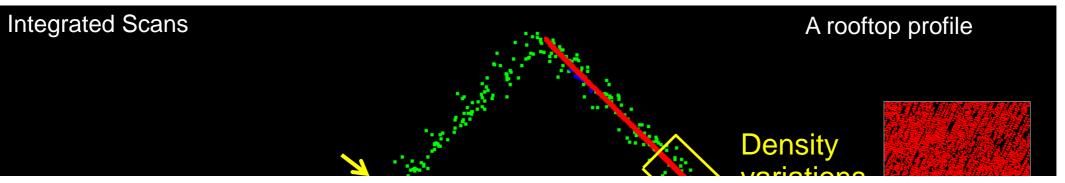




Combined and segmented scans



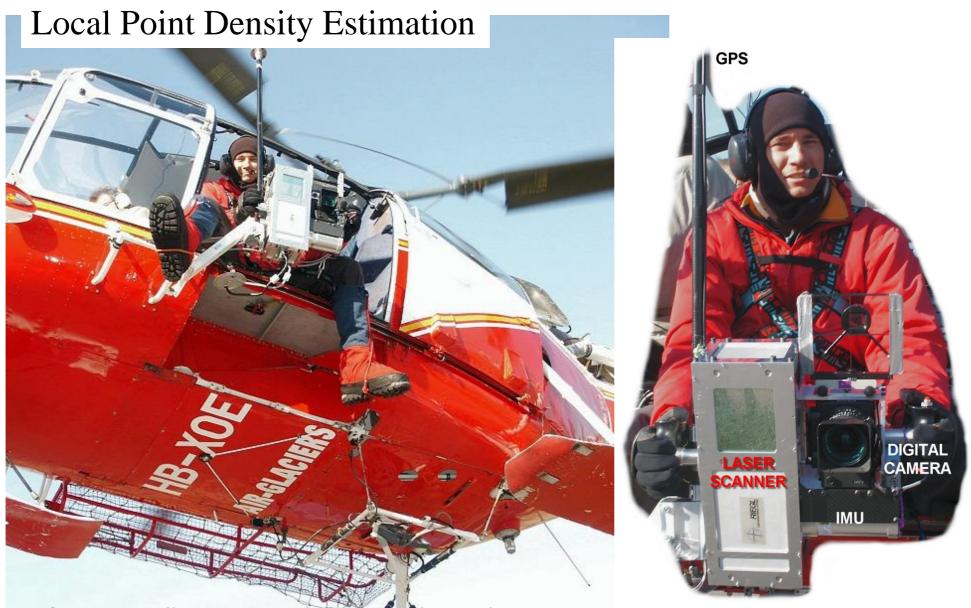
LiDAR Mapping: Ultimate Goal



We need a data characterization step to take into account the varying nature of the input point clouds.



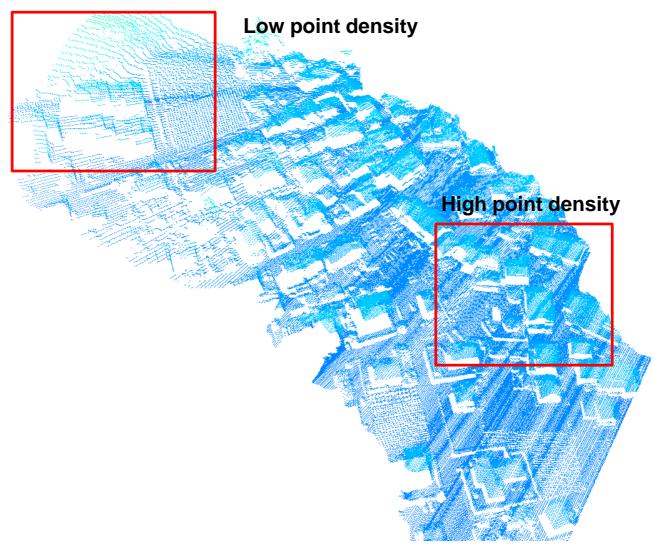




Source: http://www.isprs.org/publications/related/semana_geomatica05/front/abstracts/Dimecres9/F01.pdf



Local Point Density Estimation



Objective: Processing laser datasets with large variation in point density

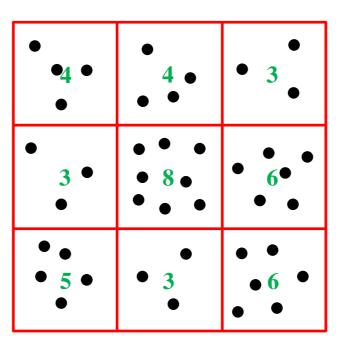


- Local Point Density Estimation:
- A measure of the average inter-point spacing along the surface it belongs to
- Local point density variations are caused by:
 - Change in the topography/elevation
 - Type of platform: terrestrial vs. airborne
 - Irregular movements of the acquisition platform
 - Number of overlapping strips
 - Scattering properties of the mapped surface



LPD Estimation: Box Counting Approach

 Box-counting method (County, 2003): Derived the point density by a "box counting", where the area of the rectangle is associated with the total number of LiDAR points inside the rectangle.

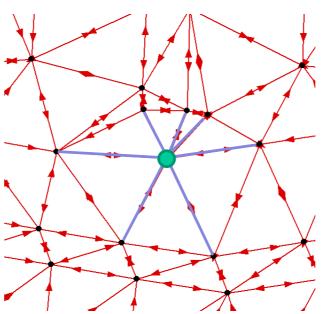


• The derived value for the local point density depends on the size and placement of the boxes. There is no standard for the determination of the box size and its placement within an area.



LPD Estimation: TIN-based Approach

- TIN-based point density determination (Shih and Huang, 2006)
 - Local point spacing determination:
 - I. Construct a Delaunay triangulation
 - II. Calculate the 2D length of every edge connecting the point in question to its neighbors
 - III.Calculate the average of the edges' lengths and record it as the local point spacing

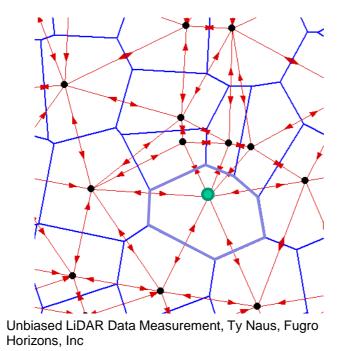


Delaunay triangulated edges for actual LiDAR points are shown in red.



LPD Estimation: TIN-based Approach

- TIN-based point density determination (Shih and Huang, 2006)
 - Local point density determination:
 - I. Construct a Voronoi diagram using constructed TIN structure
 - II. Calculate the area of the Voronoi polygon for each point
 - III. Assign the inverse of area value, or density in terms of points per unit squared, to the point



$$Area_{Voronoi\ Polygon} = \frac{1}{2} \sum_{i=0}^{n-1} (x_i y_{i+1} - x_{i+1} y_i)$$

$$Local\ Pnt\ Density = \frac{1}{Local\ Voronoi\ Polygon\ Area}$$

Voronoi polygons shown in blue for actual LiDAR points – the triangulation edges are shown in red.



LPD Estimation: Box/TIN-based approaches

Drawbacks:

- They are based on the 2D neighborhood of individual points.
- These techniques are not applicable for both airborne and terrestrial laser data (they are mainly suited for airborne data over flat/horizontal terrain).
- For the box counting technique, the derived value for the local point density depends on the size and placement of the boxes.
 - There is no standard for the determination of the cell size and its placement within an area.



Objectives:

- The local point density should be estimated while considering the 3D relationship among the points and the physical properties (planarity) of the surfaces enclosing individual points.
- In order to derive a meaningful estimate of the point density, we introduce three approaches for deciding whether the point of interest belongs to a planar surface or not:
 - Eigen value analysis of the dispersion of the points in a spherical neighborhood relative to their centroid
 - Eigen value analysis of the dispersion of the points in a spherical neighborhood relative to the point in question/point of interest (POI)
 - Adaptive cylinder approach



- Classification using Eigen value analysis of the dispersion of 3D neighboring points relative to their centroid:
 - Define a spherical neighborhood for the point of interest the neighborhood includes n points (number of points needed for reliable plane definition)
 - Calculate the dispersion matrix of the points in the spherical neighborhood relative to the centroid point $C_{3\times 3} = \frac{1}{n+1}\sum_{i=1}^{n+1}(\vec{r}_i-\vec{r}_{centroid})(\vec{r}_i-\vec{r}_{centroid})^T$

$$\vec{r}_i = [X_i \quad Y_i \quad Z_i]^T$$

$$\vec{r}_{centroid} = \frac{1}{n+1} \sum_{i}^{n+1} \vec{r}_i$$

Eigen value decomposition of the dispersion matrix

$$C = W \Lambda W^{T} = \begin{bmatrix} \vec{e}_{1} & \vec{e}_{2} & \vec{e}_{3} \end{bmatrix} \begin{bmatrix} \lambda_{1} & 0 & 0 \\ 0 & \lambda_{2} & 0 \\ 0 & 0 & \lambda_{3} \end{bmatrix} \begin{bmatrix} \vec{e}_{1}^{T} \\ \vec{e}_{2}^{T} \\ \vec{e}_{3}^{T} \end{bmatrix}$$

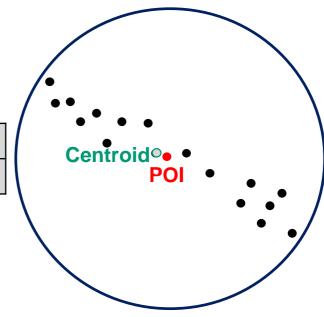
- If λ_1 (≈ 0) $\ll \lambda_2$, λ_3 the point of interest (POI) is considered to belong to a planar surface.



- Classification using Eigen value analysis of the dispersion of 3D neighboring points relative to their centroid:
 - Once the planarity of the established neighborhood is checked using the Eigen value analysis, the local point density index is calculated as follows:

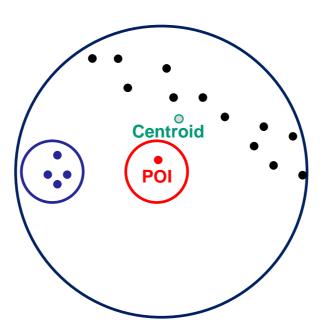
$$LPD = \frac{n+1}{\pi r_n^2}$$

	Number of points within the spherical neighborhood
r_n	The distance between the POI and its n th -farthest neighbor





- Classification using Eigen value analysis of the dispersion of 3D neighboring points relative to their centroid:
 - Disadvantages:
 - > Points that do not belong to the local planar surface (outliers) are considered in LPD estimation.
 - > Does not consider the fact that the point of interest might not belong to the local planar surface





- Classification using Eigen value analysis of the dispersion of 3D neighboring points relative to the POI:
 - Define a spherical neighborhood for the point in question which includes at least n (number of points for reliable plane definition) points
 - Calculate the dispersion matrix for the points in spherical neighborhood relative to the point of interest (POI) $C_{3\times3} = \frac{1}{n} \sum_{i=1}^{n} (\vec{r}_i \vec{r}_{POI}) (\vec{r}_i \vec{r}_{POI})^T$

$$\vec{r}_i = [X_i \quad Y_i \quad Z_i]^T$$

$$\vec{r}_{POI} = [X_{POI} \quad Y_{POI} \quad Z_{POI}]^T$$

Eigen value decomposition of the dispersion matrix

$$C = W\Lambda W^T = \begin{bmatrix} \vec{e}_1 & \vec{e}_2 & \vec{e}_3 \end{bmatrix} \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix} \begin{bmatrix} \vec{e}_1^T \\ \vec{e}_2^T \\ \vec{e}_3^T \end{bmatrix}$$

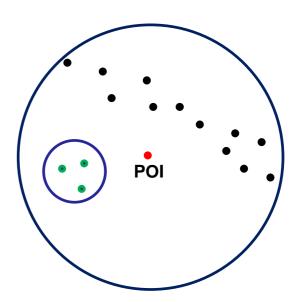
- If $\lambda_1 (\approx 0) \ll \lambda_2$, λ_3 the point of interest (POI) is considered to belong to a planar surface.



 Classification using Eigen value analysis of the dispersion of 3D neighboring points relative to the POI:

$$LPD = \frac{n+1}{\pi r_n^2}$$

<i>n</i> +1 N	umber of the points within the spherical neighborhood
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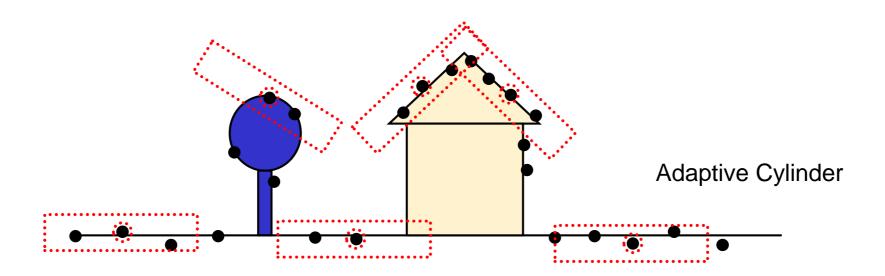
- Disadvantages:
 - > Points that do not belong to the local planar surface (outliers) are considered in LPD estimation

Classification using an adaptive cylinder:

 This approach is based on defining a cylinder, which changes its orientation with the local planar surface. This cylinder is used to decide whether the point belongs to a planar or rough surface.

Advantages:

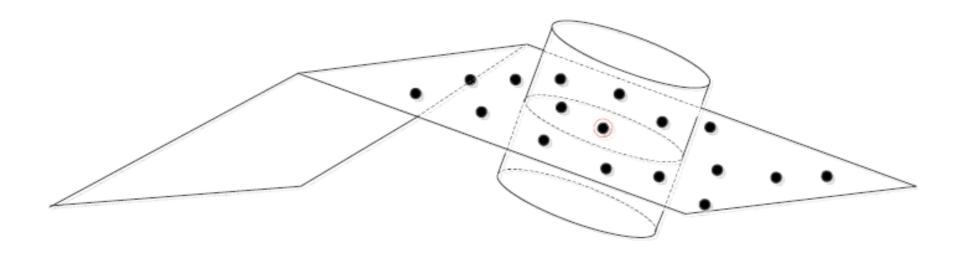
- Takes into consideration whether the point of interest belongs to the local planar surface or not
- Points that do not belong to the local planar surface (outliers) are not considered in local point density estimation.





Classification using an adaptive cylinder:

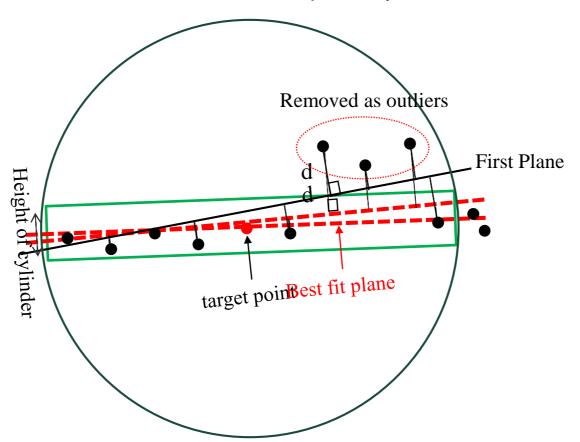
 This approach is based on defining a cylinder, which changes its orientation with the local planar surface. This cylinder is used to decide whether the point belongs to a planar or rough surface.





Classification using an adaptive cylinder:

Derivation of the Adaptive Cylinder

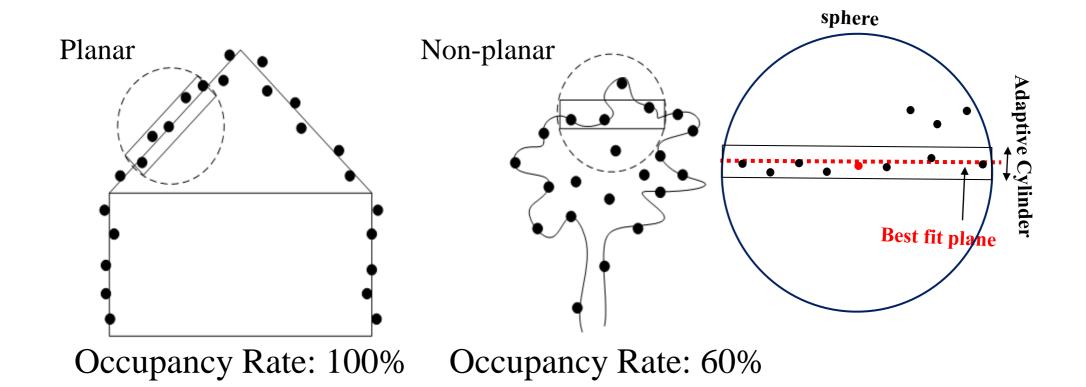


If the iterative plane fitting procedure <u>does not converge</u> within a pre-specified number of iterations, the point of interest is classified as a <u>non-planar point</u> and we will not estimate the local point density index for this point.



Classification using an adaptive cylinder:

- The point of interest should be within the adaptive cylinder, and
- The majority of the points within the spherical neighborhood should be inside the adaptive cylinder.

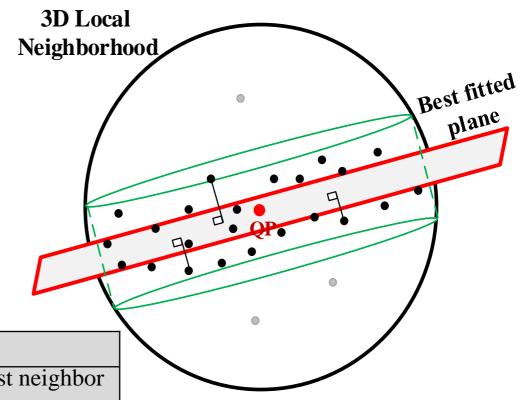




Classification using an adaptive cylinder:

 Once the planarity of the established neighborhood is checked using the adaptive cylinder, the local point density index is calculated as follows:

$$LPD = \frac{k}{\pi r_n^2}$$



K		Number of points within the adaptive cylinder
r	n	The distance between the POI and its nth-farthest neighbor

k (number of pnts in adaptive cylinder) $\leq n$ (number of pnts in sphere)



- Eigen value analysis of the dispersion matrix of the points in a spherical neighborhood relative to their centroid (Drawbacks):
 - 1. This approach classifies the neighborhood without considering the fact that the point in question might not belong to the planar neighborhood.
 - 2. Non-coplanar points are considered in LPD estimation.
- Eigen value analysis of the dispersion matrix of the points in a spherical neighborhood relative to the POI (Drawback):
 - 1. Non-coplanar points are considered in LPD estimation.
- Adaptive cylinder (Advantage):
 - Only the points that belong to the planar neighborhood are taken into consideration during the local
 point density computation while making sure that the query point belongs to the planar neighborhood.

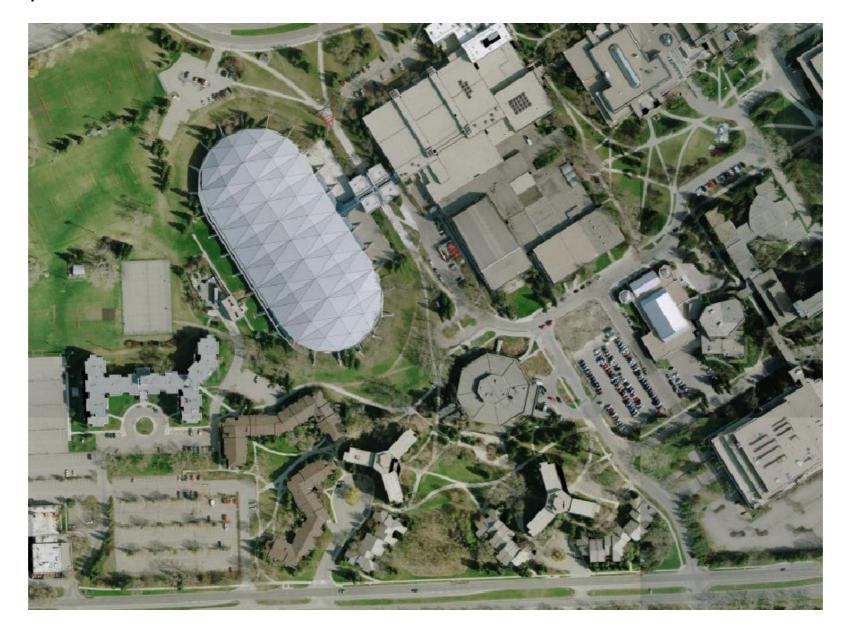


- Location: University of Calgary campus
 - Average point density: 1 pnts/m²

Threshold	Value
No. of neighboring points for Eigen-values calculation	12
No. of neighboring points for best fit plane definition	12
Height of cylinder	0.8 m
Planarity ratio	95%

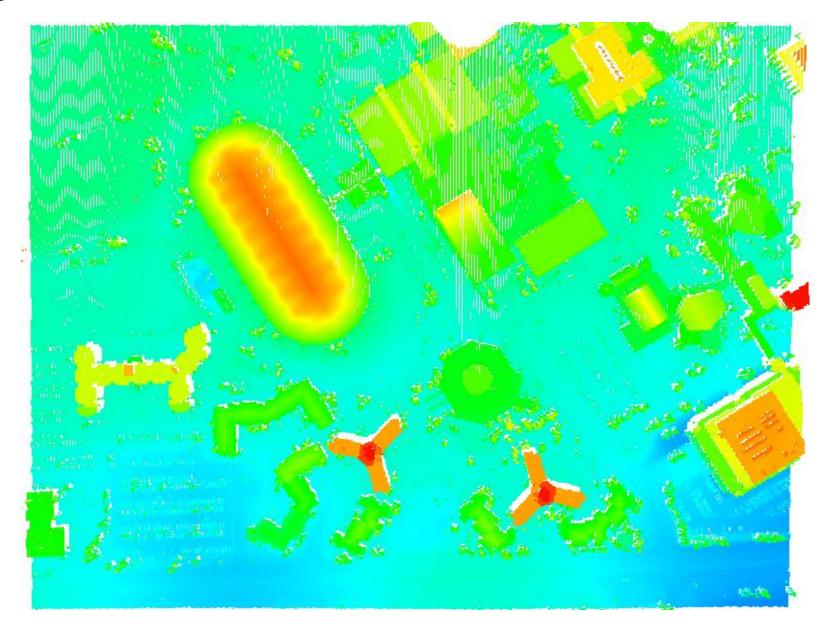


Orthophoto over the test area:



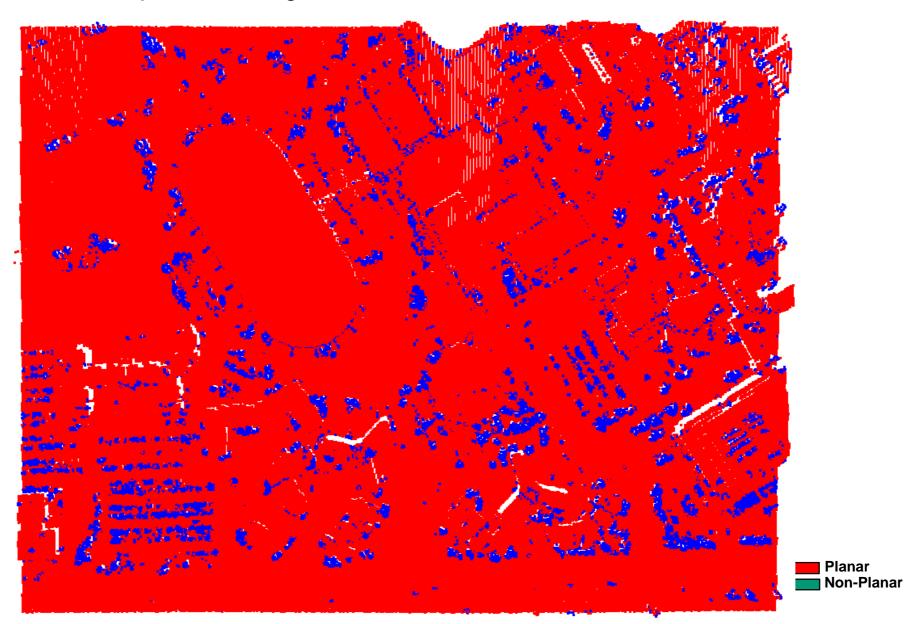


• Original LiDAR data:

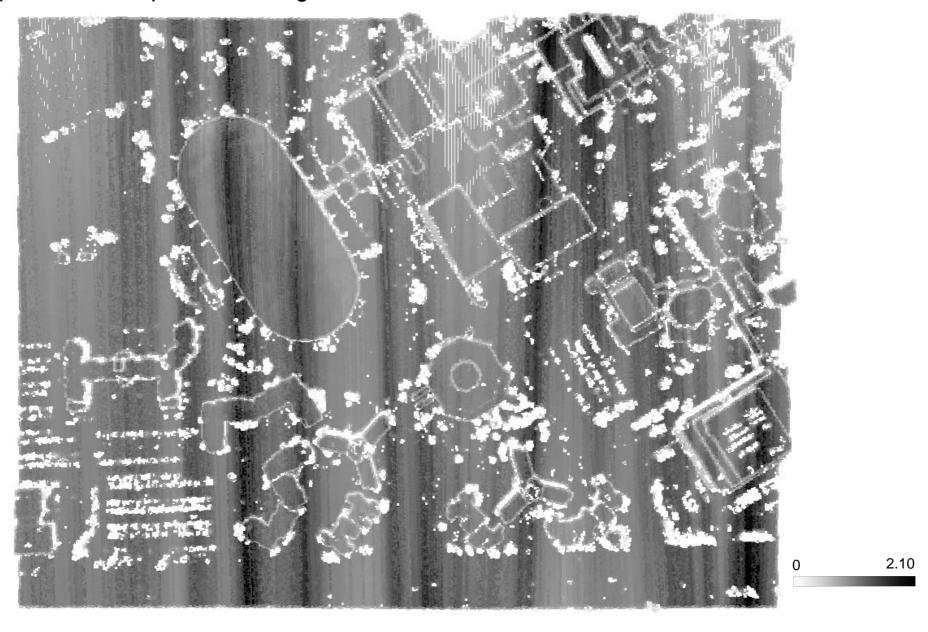




• Dispersion of the point's 3D neighbors relative to their centroid:



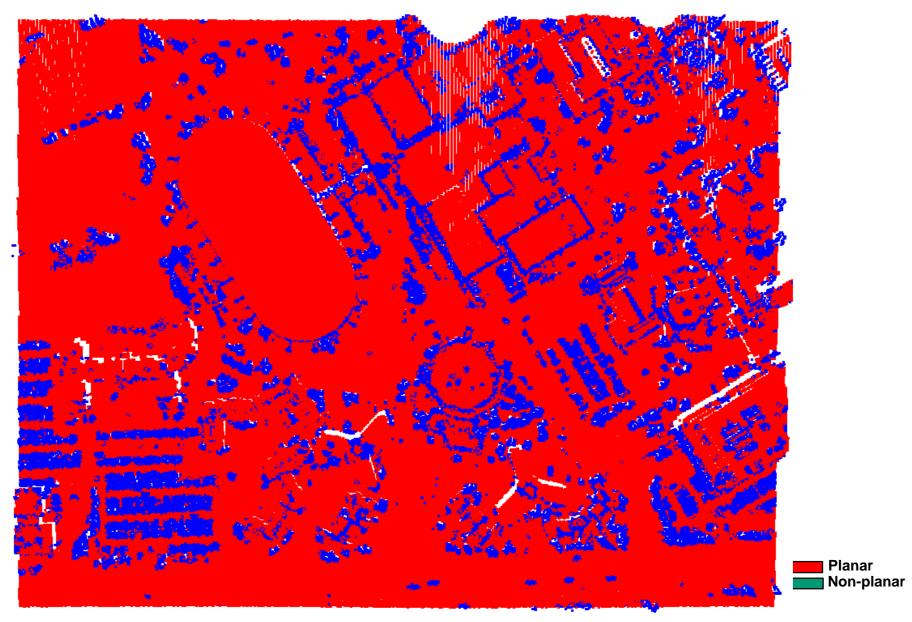
Dispersion of the point's 3D neighbors relative to their centroid:





Adaptive cylinder:

Classification Results



Adaptive cylinder:

