Chapters 1 – 6: Overview

- Photogrammetric mapping: introduction, applications, and tools
- GNSS/INS-assisted photogrammetric and LiDAR mapping
- LiDAR mapping: principles, applications, mathematical model, and error sources and their impact.
- QA/QC of LiDAR mapping
- Registration of Laser scanning data

- This chapter will be focusing on the adaptive processing of LiDAR data.
  - Point cloud characterization
  - Segmentation and feature extraction

Chapter 7

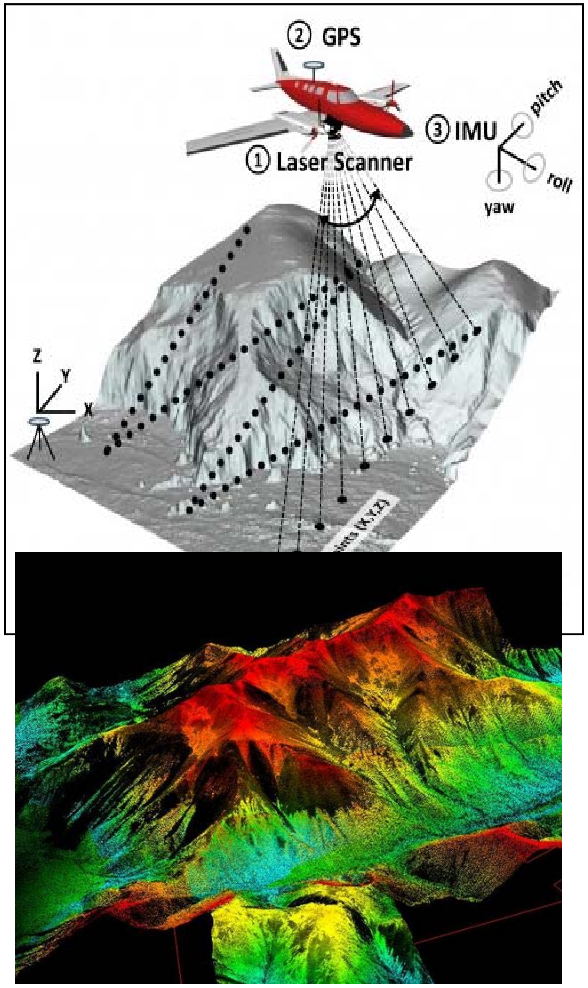
ADAPTIVE PROCESSING OF LIDAR DATA FOR EXTRACTING PLANAR/LINEAR FEATURES

Overview

- LiDAR Mapping Principles
- LiDAR Data Structuring
- LiDAR Data Characterization
  - Local Point Density (LPD) Estimation
- Planar & Linear Feature Segmentation
  - Spatial-Domain Segmentation
  - Parameter-Domain Segmentation
  - Quality Control of the Segmentation Outcome
- Concluding Remarks
- Current & Future Work

LiDAR Mapping

Airborne Laser Scanning



Static Terrestrial Laser Scanning

Kinematic Terrestrial Laser Scanning

LiDAR Mapping

Tripod mounted scanners VZ-6000

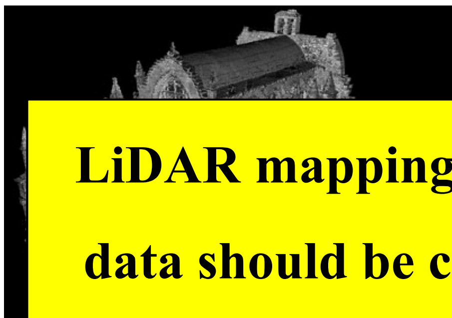
Mobile laser scanners VMX-250

Airborne laser scanners (ALS) ALTM Gemini

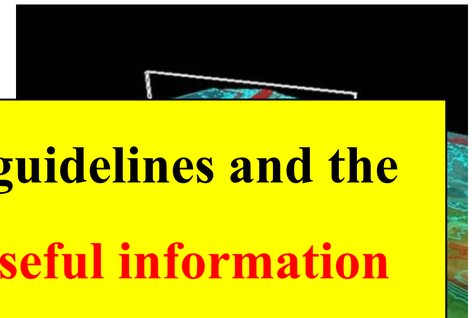
Photos courtesy of RIEGL Laser Measurement Systems, and Optech Inc.

LiDAR Mapping

Heritage Documentation

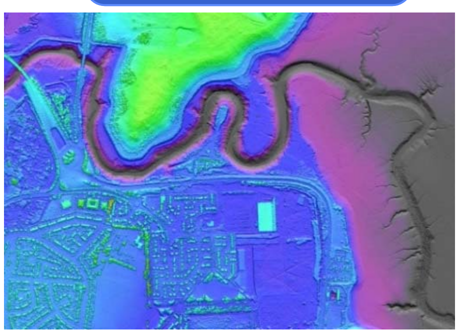


Transportation Planning



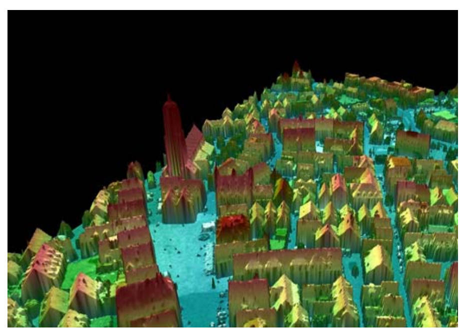
LiDAR mapping should have reliable QA/QC guidelines and the data should be carefully processed to extract useful information for these applications.

Flood Plain Mapping



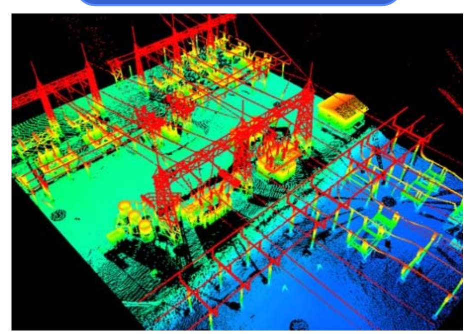
Source: www.maritimejournal.com

3D City Modeling



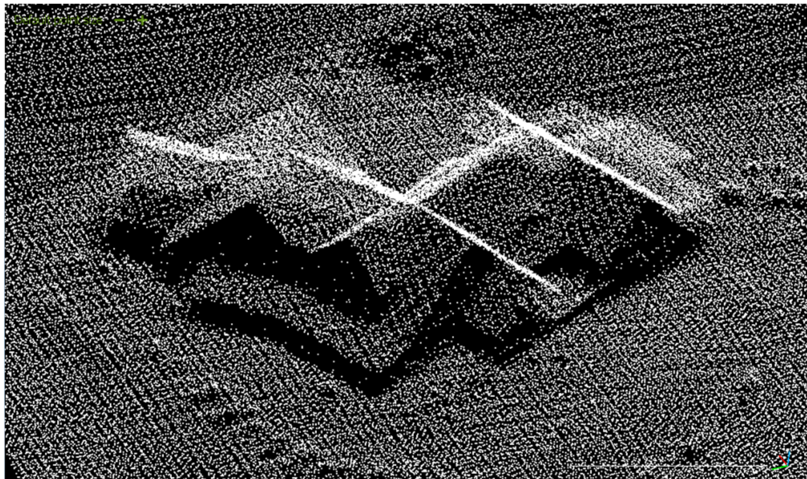
Source: www.trimble.com

Power–Line Mapping

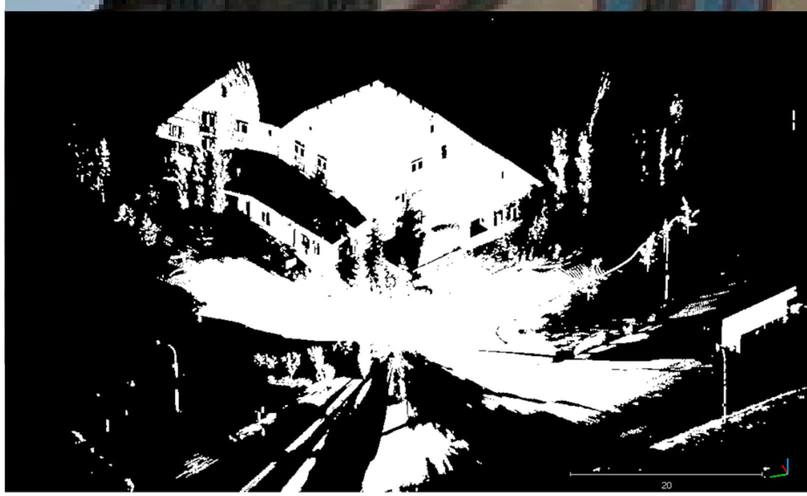


Source: www.merrick.com

LiDAR Mapping: Ultimate Goal



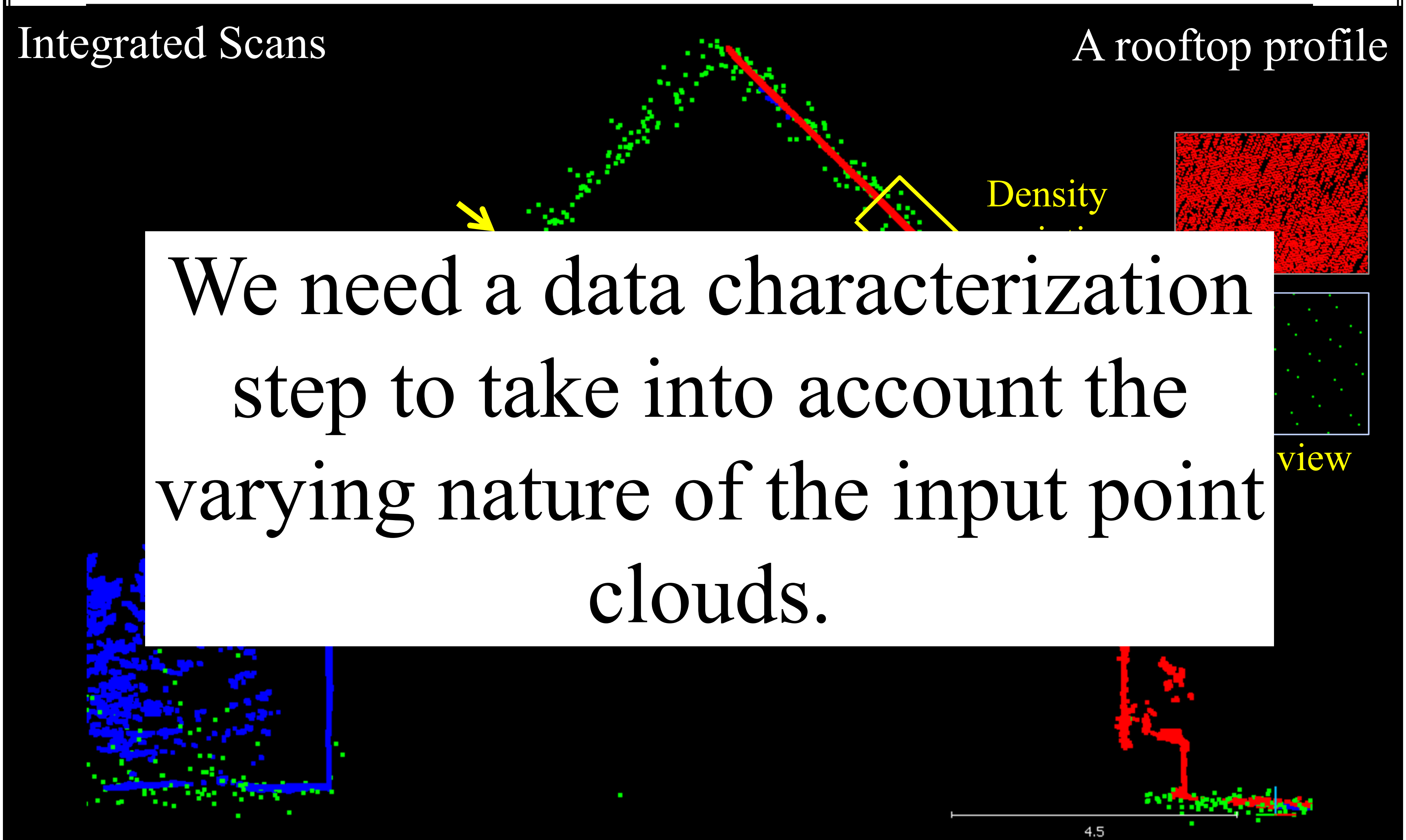
Airborne scan



Terrestrial scan

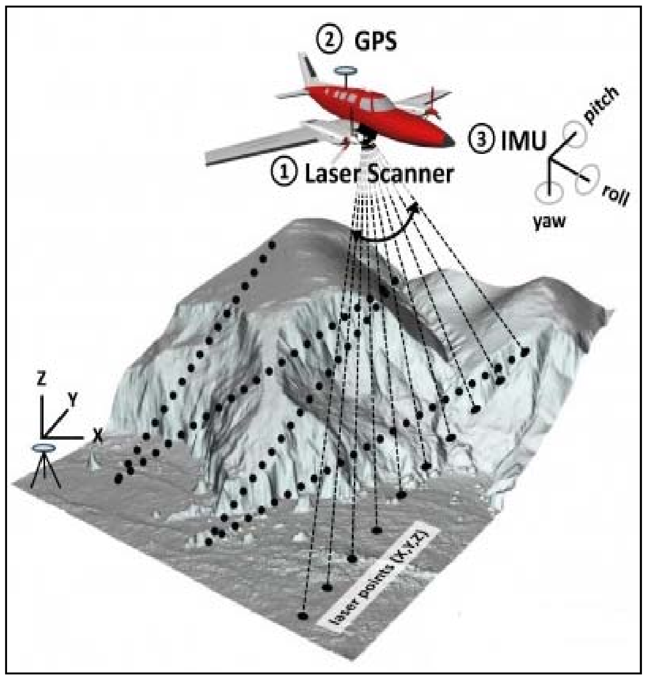
Combined and segmented scans

LiDAR Mapping: Ultimate Goal



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

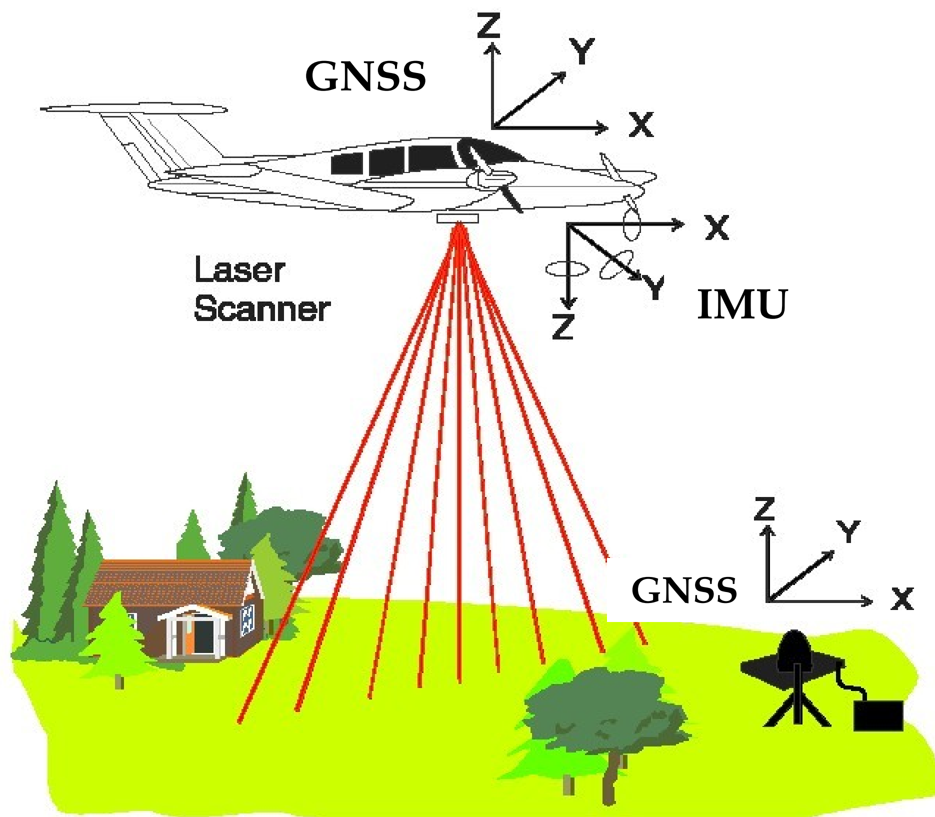
Airborne LiDAR Mapping



Airborne LiDAR Mapping

Three Measurement Systems

1. GNSS
2. IMU
3. Laser scanner emits laser beams with high frequency and collects the reflections.



Airborne LiDAR Mapping

Operational LiDAR Systems

ALS 60 (Leica Geosystems)

Airborne LiDAR Mapping

Operational LiDAR Systems

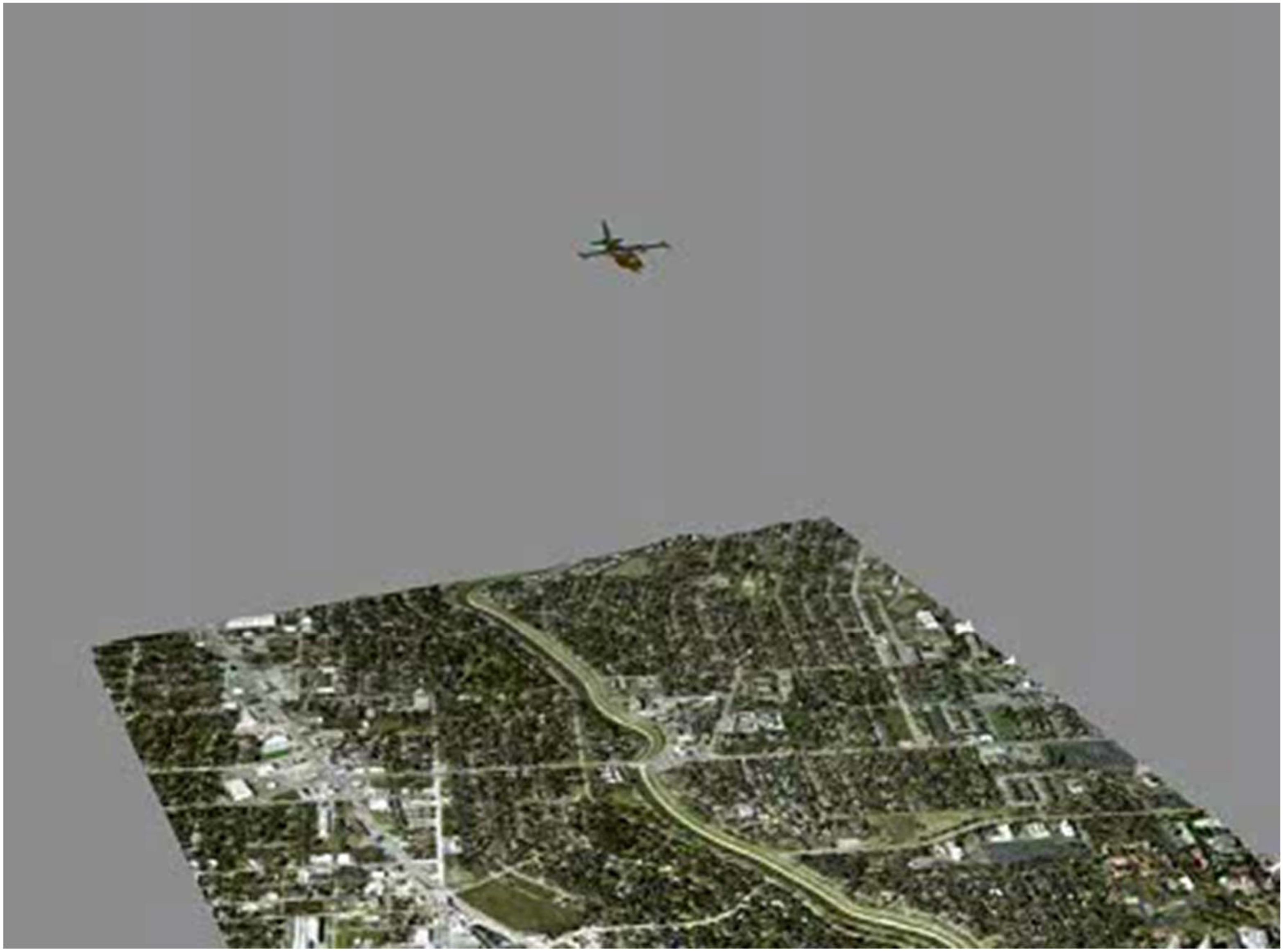
OPTECH ALTM GEMINI

Airborne LiDAR Mapping

Operational LiDAR Systems

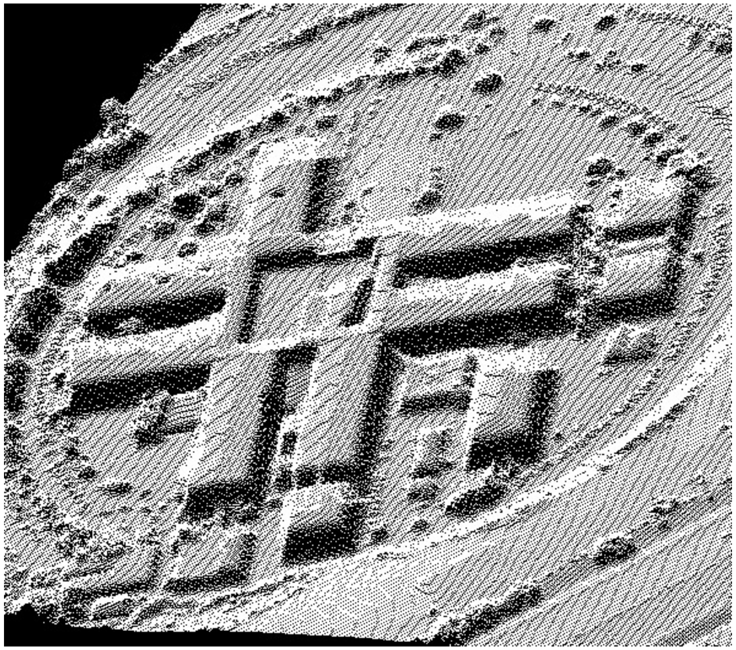
long-range *RIEGL* LMS-Q680i

Airborne LiDAR Mapping

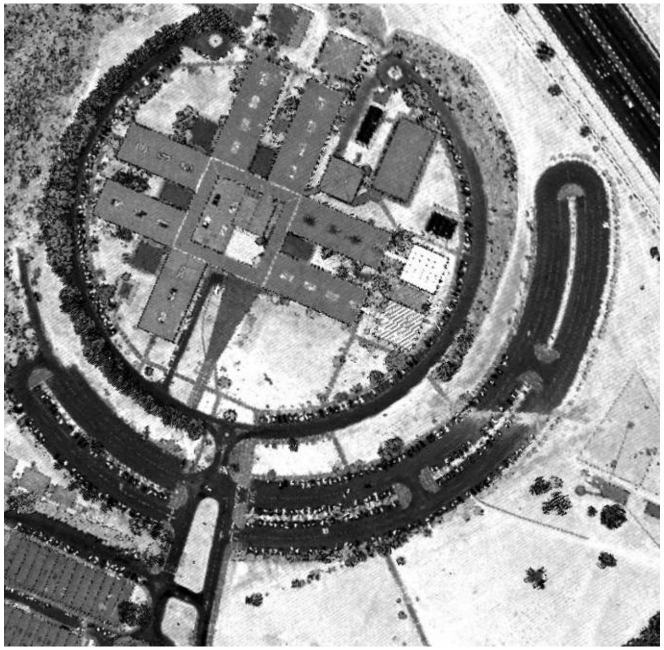


Airborne LiDAR Mapping

- LiDAR produces accurate point cloud along object-space surfaces in addition to intensity images.

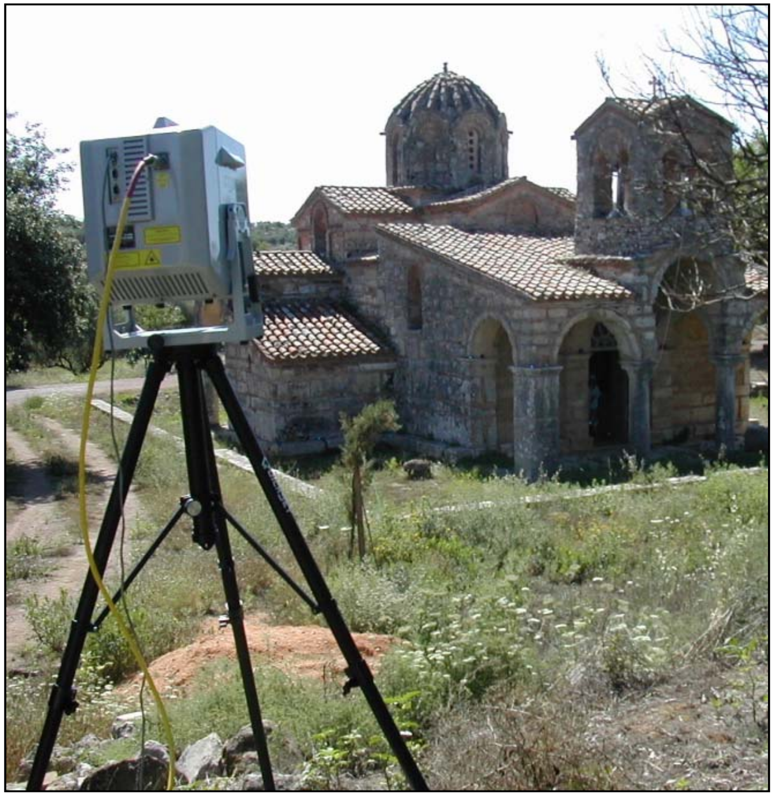


Elevation Data



Intensity Image

Static Terrestrial Laser Scanning



Static Terrestrial Laser Scanning

Time of Flight Systems

Pulse Based

Hybrid Type

Trimble, http://www.trimble.com/trimblegx.shtml, (accessed March 16, 2010)

Phase Based

Panoramic Type

Leica Geosystems, http://hds.leica-geosystems.com/en/index.htm, (accessed October 7, 2009)

Triangulation Based

Camera Type

Konica Minolta, http://www.konicaminolta.com/instruments/products/3d/index.html, (accessed October 7, 2009)

Accuracy

1mm → 0.01mm

Range

100m ← 10m ← 1m

Static Terrestrial Laser Scanning

- A static terrestrial laser scanner (pulse/phase-based) is an automatically driven total station/EDM.
- It measures distances to objects at uniform increments in the horizontal and vertical directions.
- These measurements are then converted into a Cartesian coordinate system.
- Most terrestrial laser scanners would even provide intensity and RGB values, although this is not always the case.

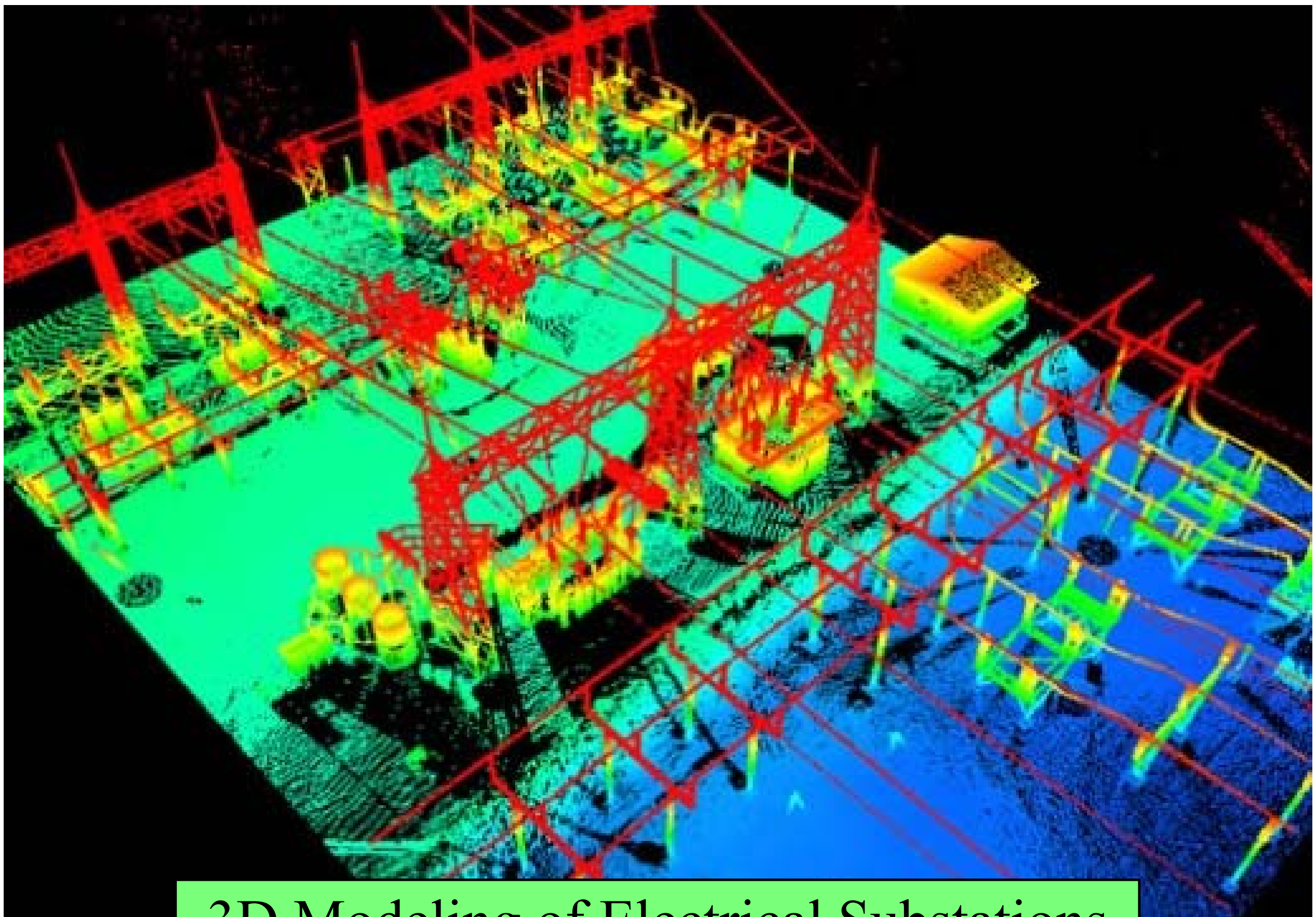
Static Terrestrial Laser Scanning


Examples of Operational Systems:
Mensi GS200, Leica (Cyrax) HDS3000, Riegl LMS Z210

Static Terrestrial Laser Scanning

Landslide Hazard Analysis

Static Terrestrial Laser Scanning



3D Modeling of Electrical Substations

Kinematic Terrestrial Laser Scanning

Kinematic Terrestrial Laser Scanning

Source: http://www.streetmapper.net/

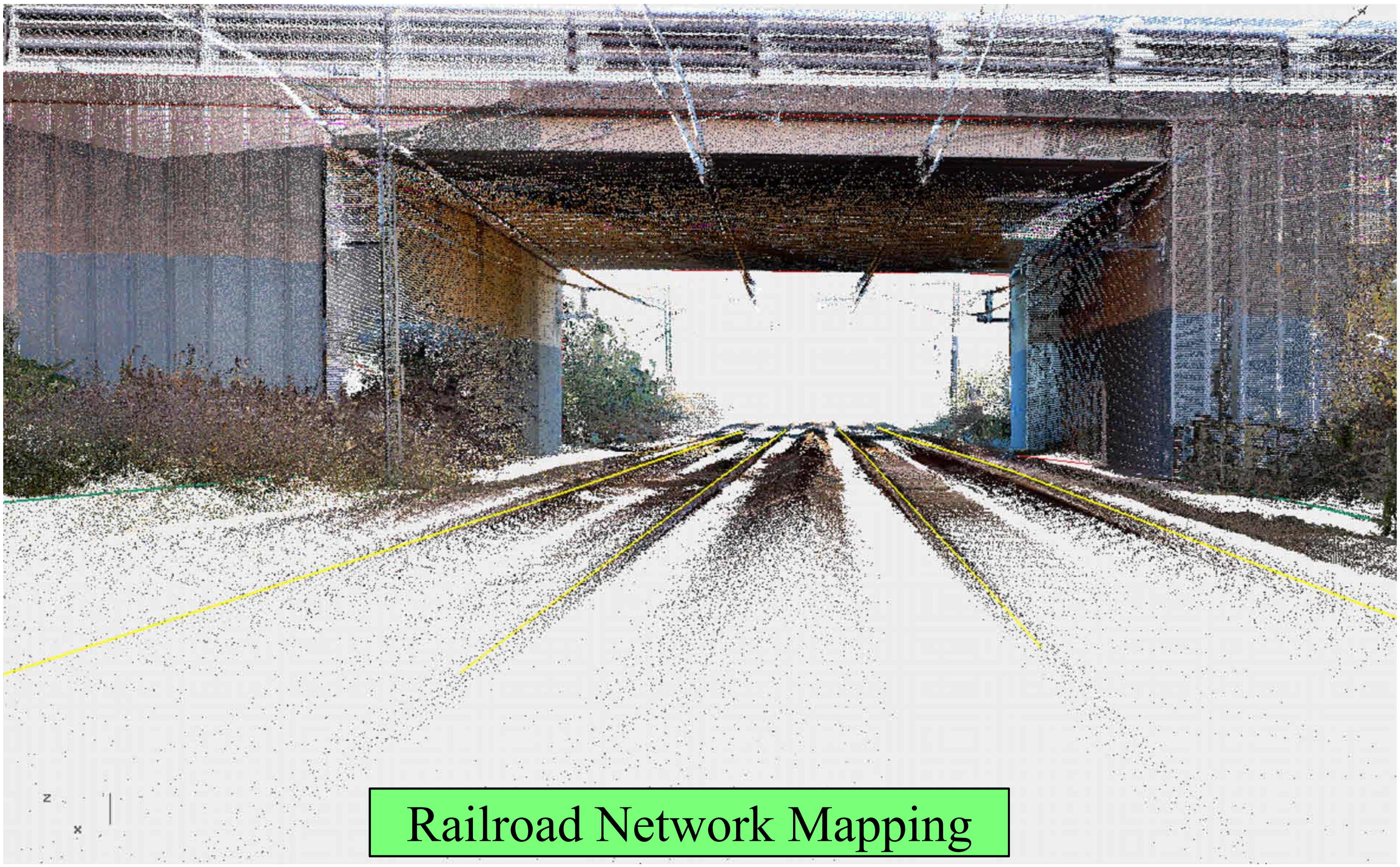
Source: http://www.riegl.com/uploads/tx_pxpriegldownloads/10_DataSheet_RIEGL_VMX-250_08-04-2010_PRELIMINARY_pdf.pdf

Kinematic Terrestrial Laser Scanning

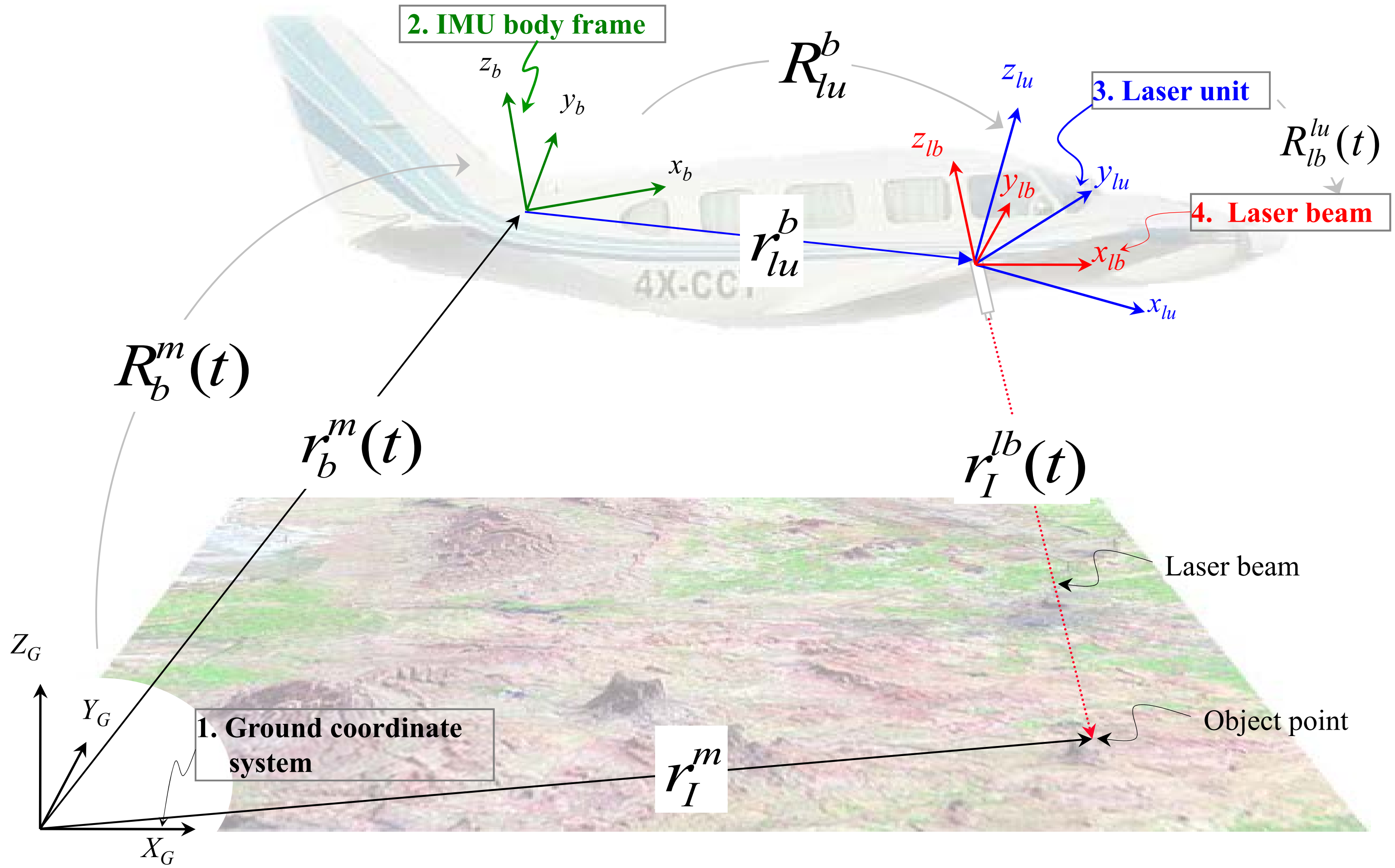
Road Furniture Mapping

Kinematic Terrestrial Laser Scanning

Kinematic Terrestrial Laser Scanning



LiDAR Equation & Coordinate Systems



- LiDAR equation is a vector summation procedure.

LiDAR Equation

$$r_I^m = r_b^m(t) + R_b^m(t)\ r_{lu}^b + R_b^m(t)\ R_{lu}^b\ R_{lb}^{lu}(t)\, r_I^{lb}(t)$$

r_I^m	ground coordinates of the object point under consideration
$r_b^m(t)$	ground coordinates of the origin of the IMU coordinate system
$R_b^m(t)$	rotation matrix relating the ground and IMU coordinate systems
r_{lu}^b	offset between the laser unit and IMU coordinate systems (lever arm offset)
R_{lu}^b	rotation matrix relating the IMU and laser unit coordinate systems (boresight matrix)
$R_{lb}^{lu}(t)$	rotation matrix relating the laser unit and laser beam coordinate systems
$r_I^{lb}(t)$	coordinates of the object point relative to the laser beam coordinate system

- Note: There is no redundancy in the surface reconstruction process.

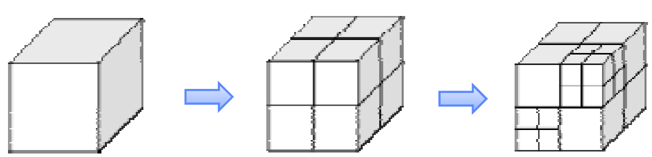
LiDAR Data Structuring

kd-Structure

Structuring the Laser Points

- Objectives:
  - Efficient sorting and organization of laser points
  - Speed up the process of searching for the nearest neighbour(s) of a point
- Data structures:
  - **Delaunay triangulation**: A triangulation of the laser point cloud divides its convex hull into a set of triangles. A circle passing through the vertices of any triangle doesn't contain any other point of the point set (Okabe et al., 1992).
    - × This structure is defined in the XY-plane and does not consider the points' heights.

  - **Octree data structure**: Octrees are used to partition a three-dimensional space by recursively subdividing it into eight subspaces.
    - × It cannot guarantee a fully balanced hierarchical data structure.



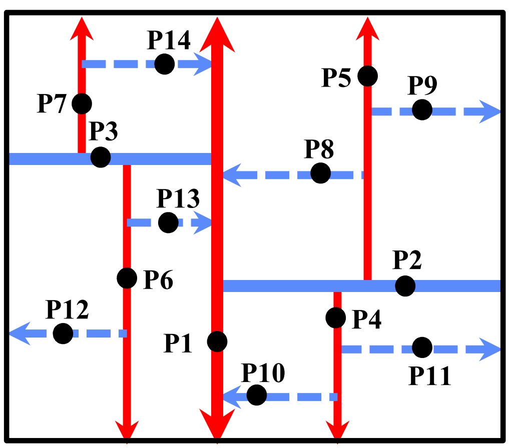
Structuring the Laser Points: kd-Tree Structure

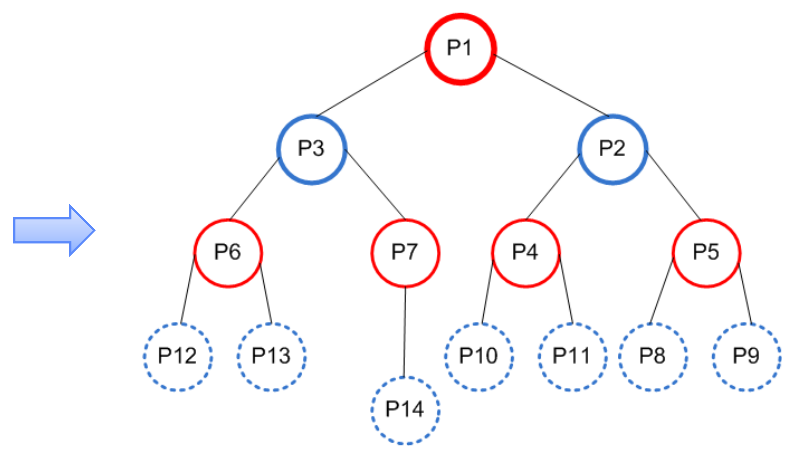
- **kd-tree data structure construction:**
  - Recursive subdivision of the three-dimensional space along the longest extent of the data in the X, Y, or Z direction
  - The splitting plane is perpendicular to the chosen extent direction and passes through the point with the median coordinate along the selected extent (Sadgewick, 1992).
- **Advantages**

✓ Efficient structuring with minimal number of subdivisions

✓ More efficient nearest neighbour search algorithms

✓ Balanced data structure





Searching for the Nearest Neighbour of a Point

- Nearest neighbour of a given point

I. Start with the root node, the algorithm moves down the tree recursively in the same way it would if the point in question were being inserted.

II. Initial distance (infinity) is reduced as closer points are discovered.

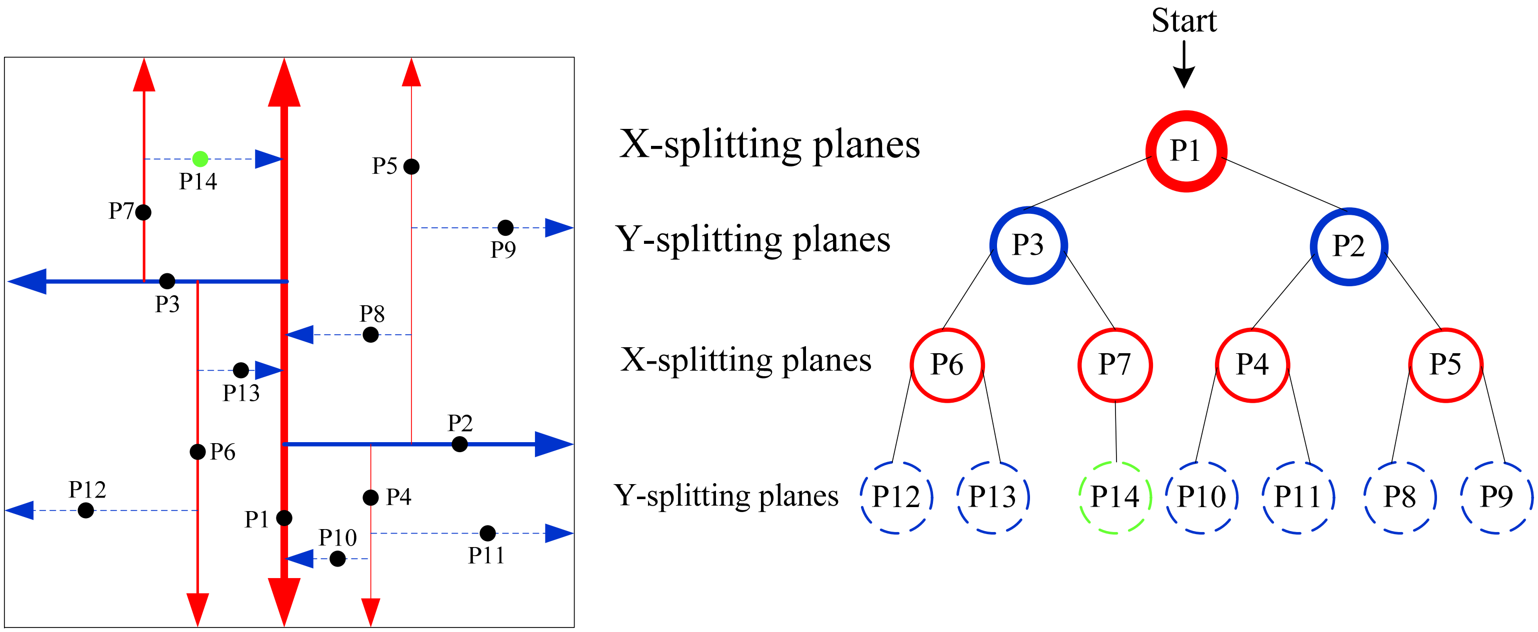
III. Steps I and II are repeated until the algorithm reaches the leaf node.

IV. Search the other side of the splitting plane for points which may be closer to the point in question by checking the intersection of the splitting hyper plane with a sphere centered at the point in question with a radius equivalent to the distance to the closest discovered point. In case of intersection between them, the other branch of the tree should also be searched for a closest neighbour.

V. The node with the smallest distance is returned as the nearest neighbour.

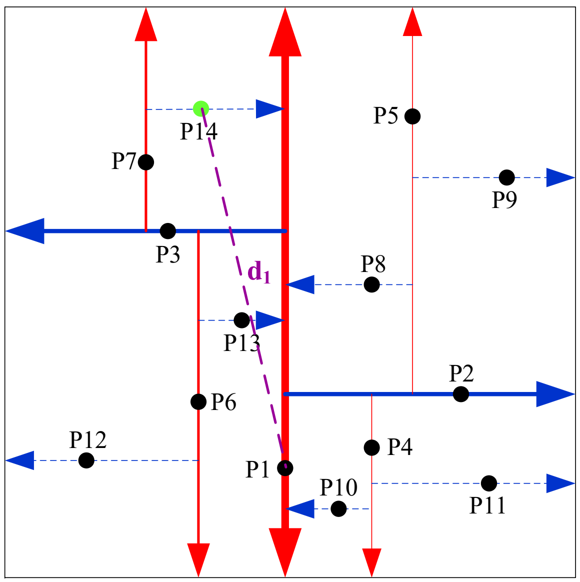
Searching for the Nearest Neighbour of a Point

- Nearest neighbour of a given point (P14): Schematic view

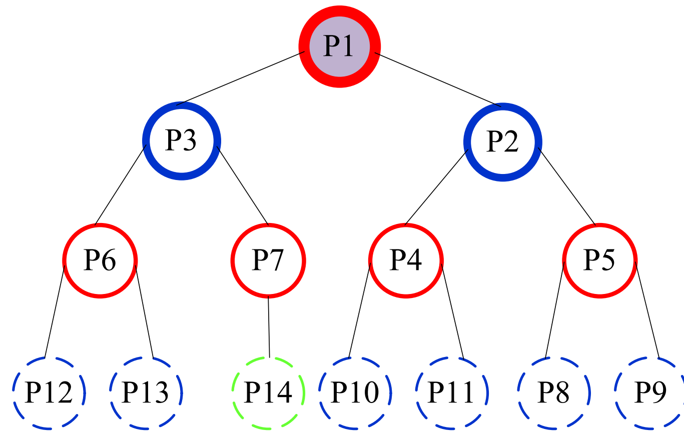


Searching for the Nearest Neighbour of a Point

- Nearest neighbour of a given point (P14): Schematic view



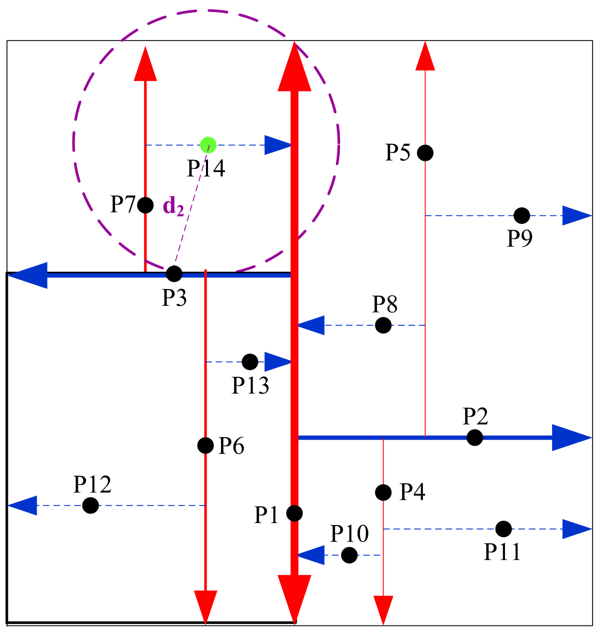
Candidate Point = P1
Minimum Distance = d_1



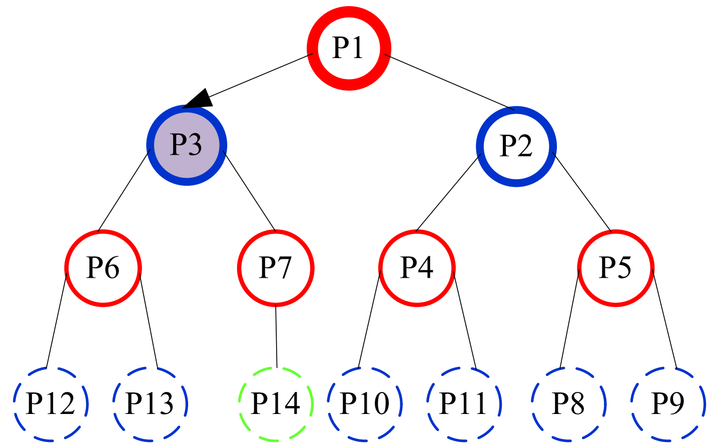
Since P14 is on the left hand side of P1, the left hand side of P1 is traced for nearest neighbour first.

Searching for the Nearest Neighbour of a Point

- Nearest neighbour of a given point (P14): Schematic view



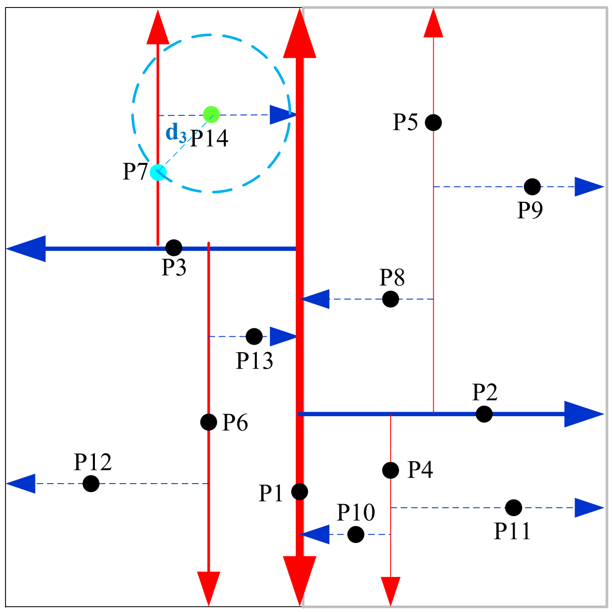
Candidate Point = P3
Minimum Distance = d_2



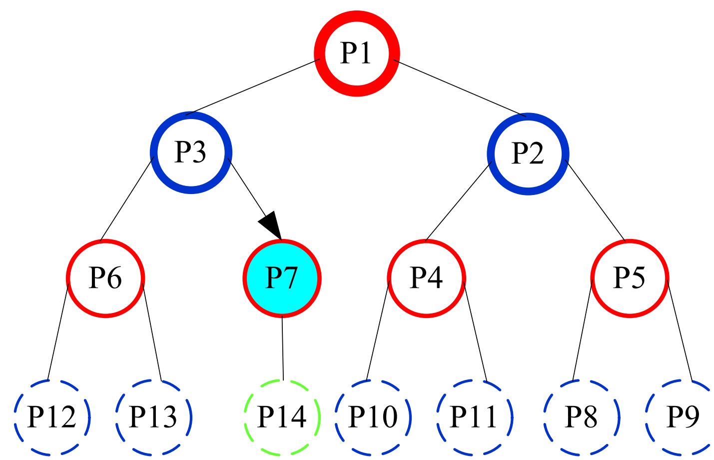
Since P14 is on the right hand side of P3, the right hand side of P3 is traced for nearest neighbour first.

Searching for the Nearest Neighbour of a Point

- Nearest neighbour of a given point (P14): Schematic view



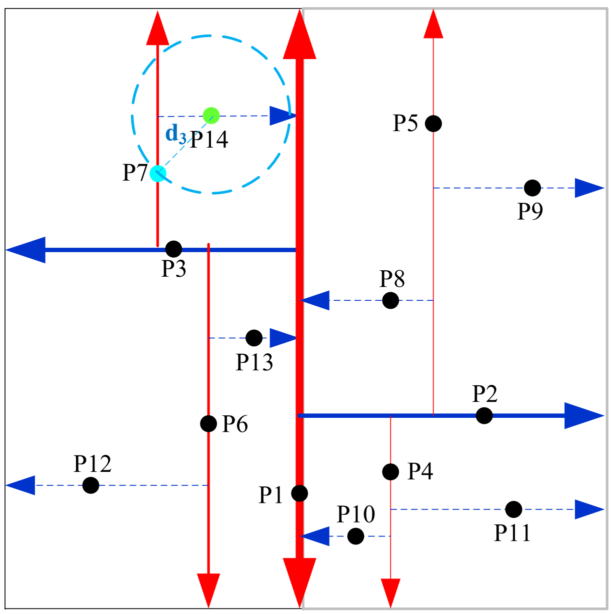
Candidate Point = P7
Minimum Distance = d_3



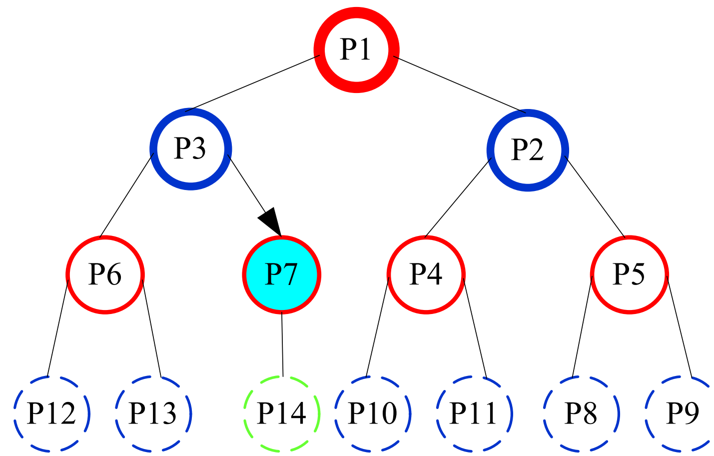
Since P14 is on the right hand side of P7, the right hand side of P7 is traced for nearest neighbour first.

Searching for the Nearest Neighbour of a Point

- Nearest neighbour of a given point (P14): Schematic view



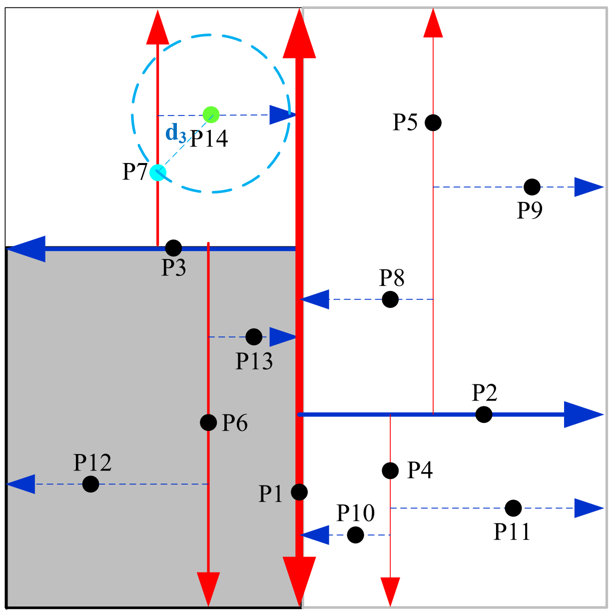
Candidate Point = P7
Minimum Distance = d_3

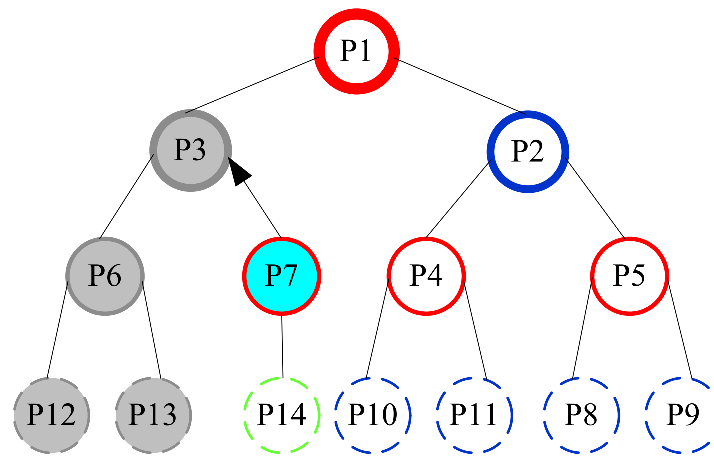


The hyperplane passing through P7 intersects the sphere, with radius equivalent to the minimum distance, centered at the point of interest, We should also check the left hand side of P7 for the nearest neighbour (there is not any node on the left hand side of P7).

Searching for the Nearest Neighbour of a Point

- Nearest neighbour of a given point (P14): Schematic view



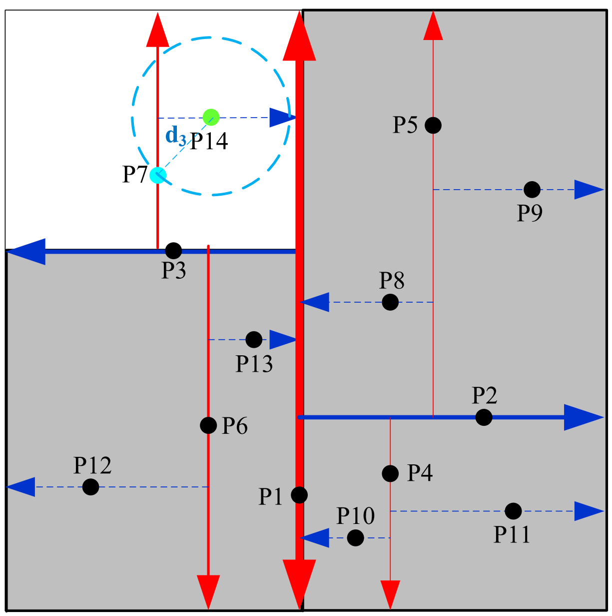


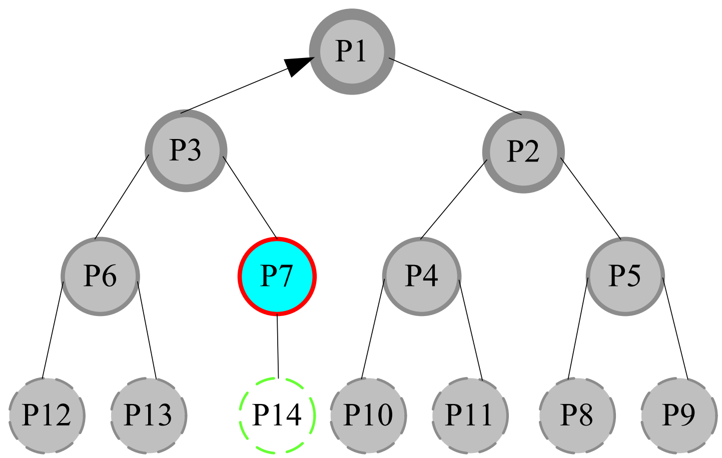
Candidate Point = P7
Minimum Distance = d_3

Since the hyperplane passing through P3 does not intersect the sphere, with radius equivalent to the minimum distance, centered at the point of interest, there is no need to check the left hand side of P3 for the nearest neighbour.

Searching for the Nearest Neighbour of a Point

- Nearest neighbour of a given point (P14): Schematic view





Nearest Neighbour Point = P7
Minimum Distance = d_3

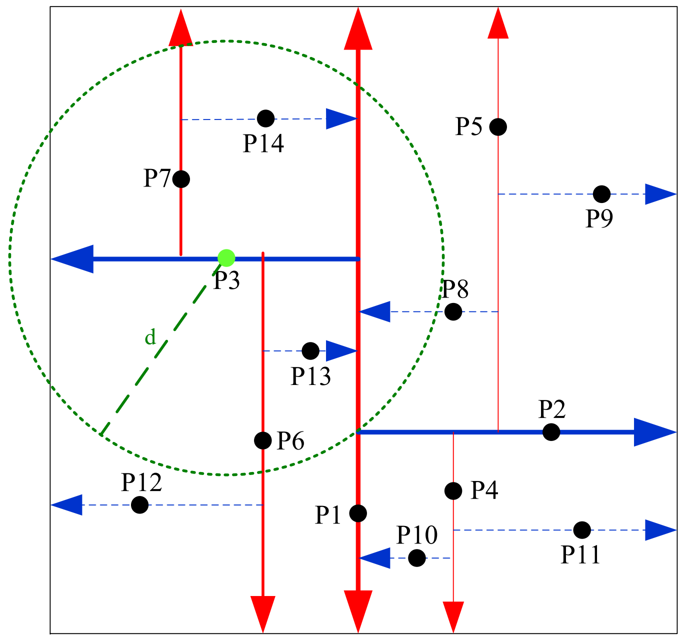
Since the hyperplane passing through P1 does not intersect the sphere, with radius equivalent to the minimum distance, centered at the point of interest, there is no need to check the right hand side of P1 for the nearest neighbour.

Searching for N. N. of a Point in a Given Range

- This is implemented by a modified nearest neighbour search. The modifications are:
  I. Start with the root node, the algorithm moves down the tree recursively in the same way it would if the point in question were being inserted (Initial distance is not reduced as closer points are discovered)
  II. Steps I is repeated until the algorithm reaches the leaf node.
  III. Search the other side of the splitting plane for points with distances less than the defined range by checking the intersection of the splitting hyper plane with a sphere centered at the point in question with a radius equivalent to the defined range. In case of intersection between them, the other branch of the tree should also be searched.
  IV. All discovered points within the defined range "**d**" are returned.

Searching for N. N. of a Point in a Given Range

- This is implemented by a modified nearest neighbour search. The modifications are:
  - Initial distance is not reduced as closer points are discovered.
  - All discovered points within the distance **d** are returned.



Searching for k Nearest Neighbours of a Point

I. Find the nearest neighbour of the point in question

II. Compute the distance between the point in question and its nearest neighbour

III. Calculate the radius for a new search by assuming a square whose dimensions are $\sqrt{k}d \times \sqrt{k}d$, where d is the distance to the nearest neighbour

$$r = \frac{\sqrt{2}\sqrt{k}d}{2} = \frac{\sqrt{2k}}{2}d$$

IV. Find the neighbouring points in a spherical neighbourhood with radius ***r*** centered at the point in question

V. If less than ***k*** points are found in the spherical neighbourhood, the search radius is increased until at least ***k*** points are found in the defined neighbourhood.

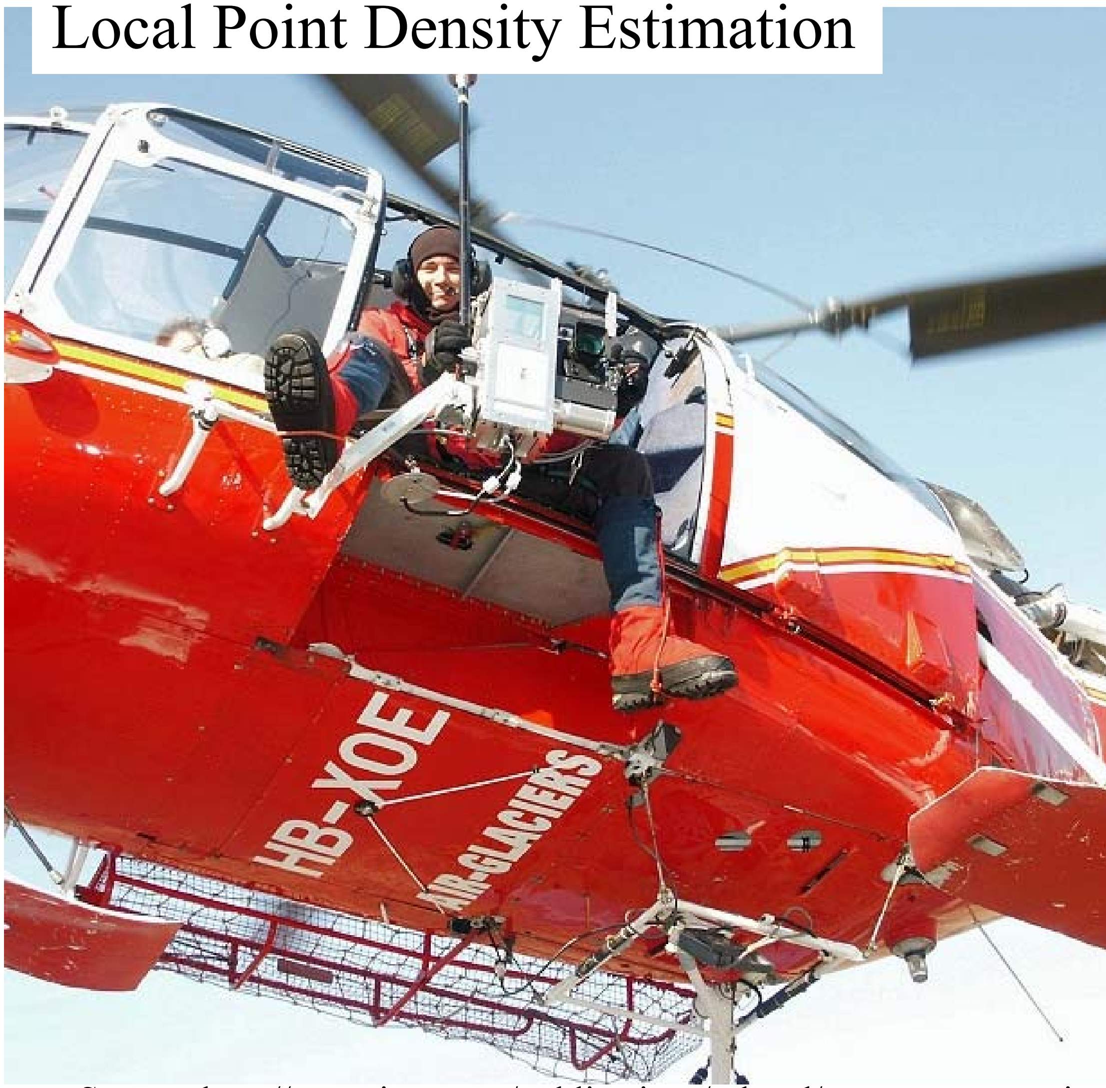
VI. If more than ***k*** points are found in the spherical neighbourhood, only the ***k*** nearest neighbours are returned.

LiDAR Data Characterization

Local Point Density Estimation

LiDAR Data Characterization

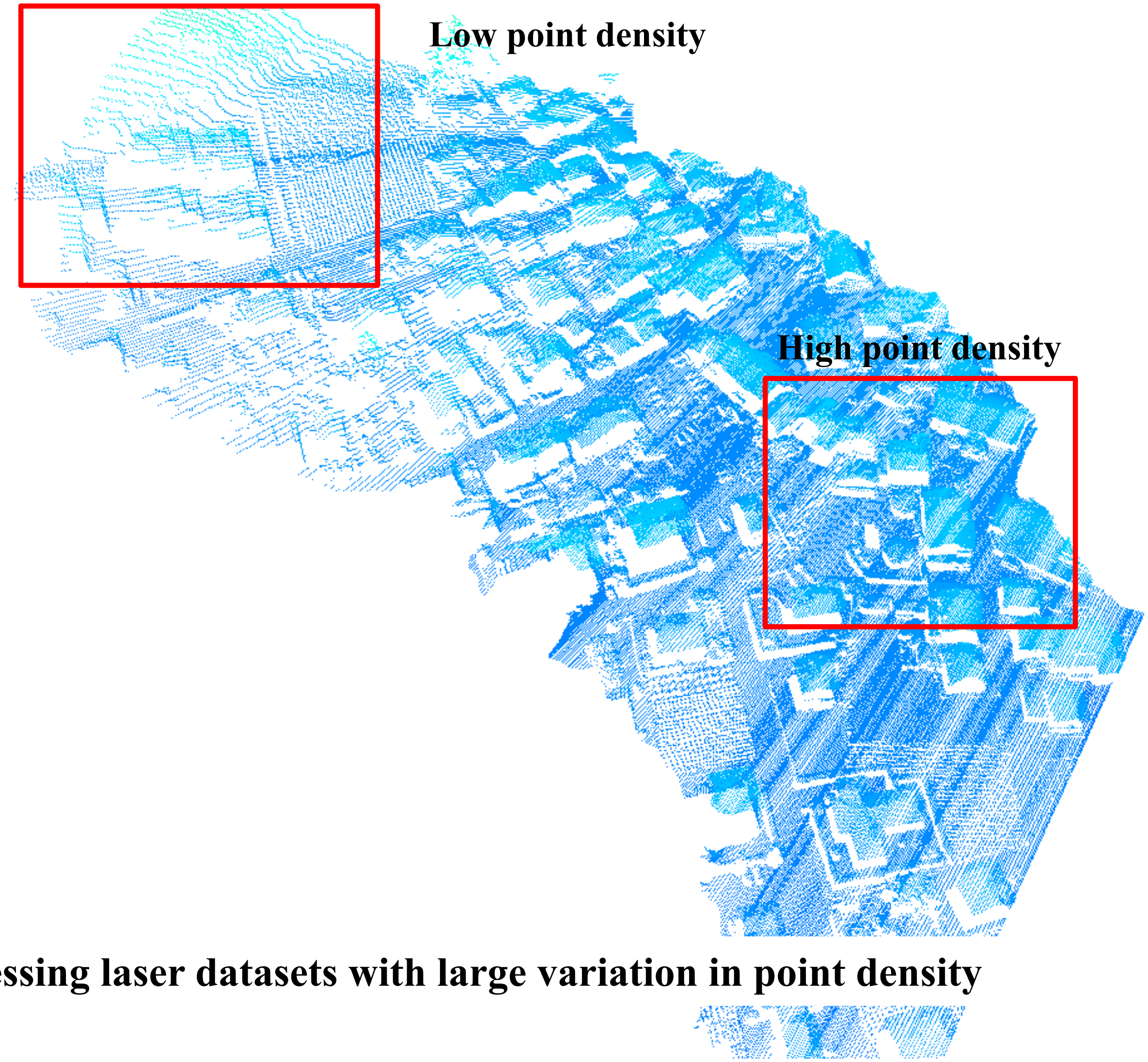
Local Point Density Estimation



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

LiDAR Data Characterization

Local Point Density Estimation



Objective: Processing laser datasets with large variation in point density

LiDAR Data Characterization

Local Point Density Estimation

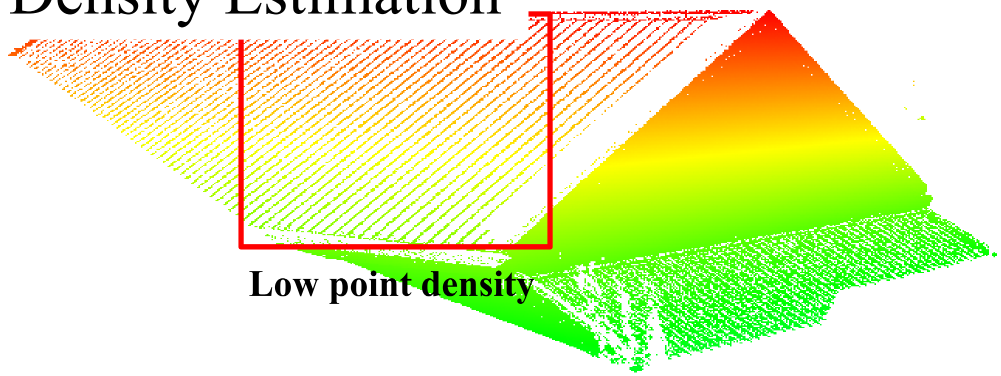
FARO Focus3D X 330
976,000 points/second
330m range
±2mm range error
*http://faro.com

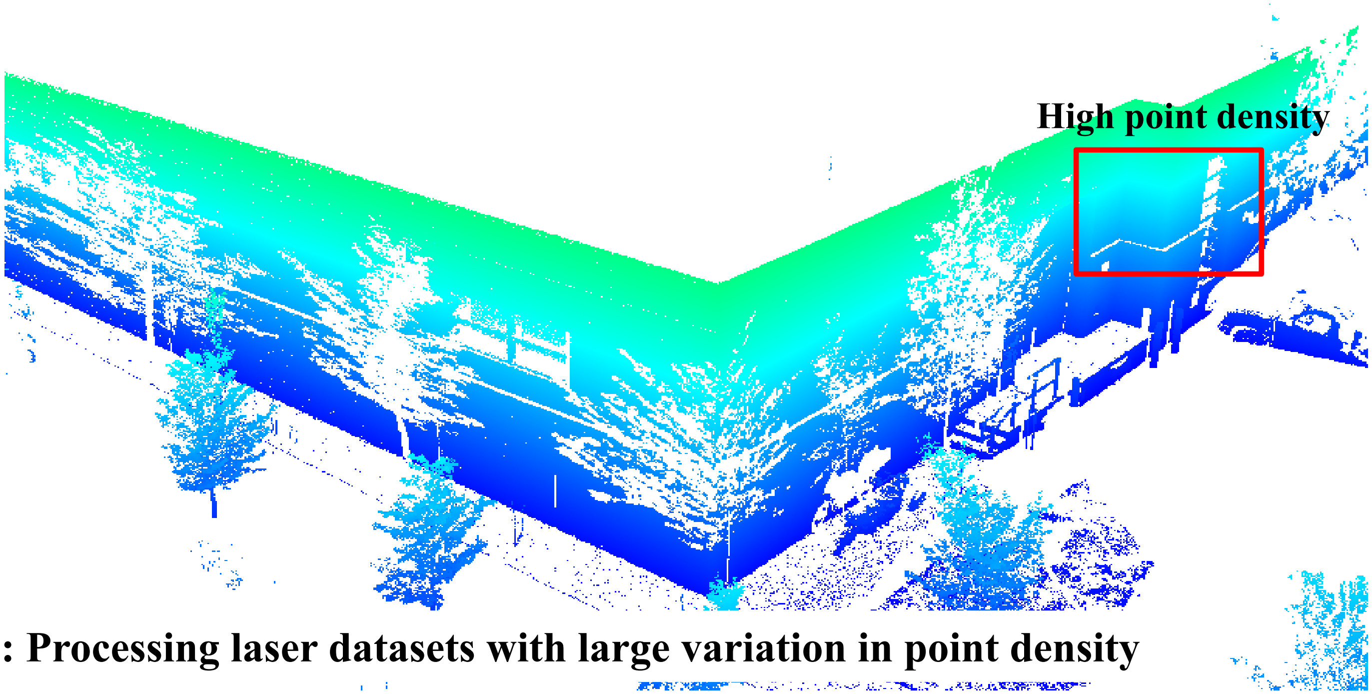
Leica Scanner P20
1 million points/second
120m range
±6mm at100m position error
*http://leica-geosystems.com

- Static Terrestrial Laser Scanner (STLS) refers to LiDAR equipment that is mounted on a tripod.

LiDAR Data Characterization

Local Point Density Estimation



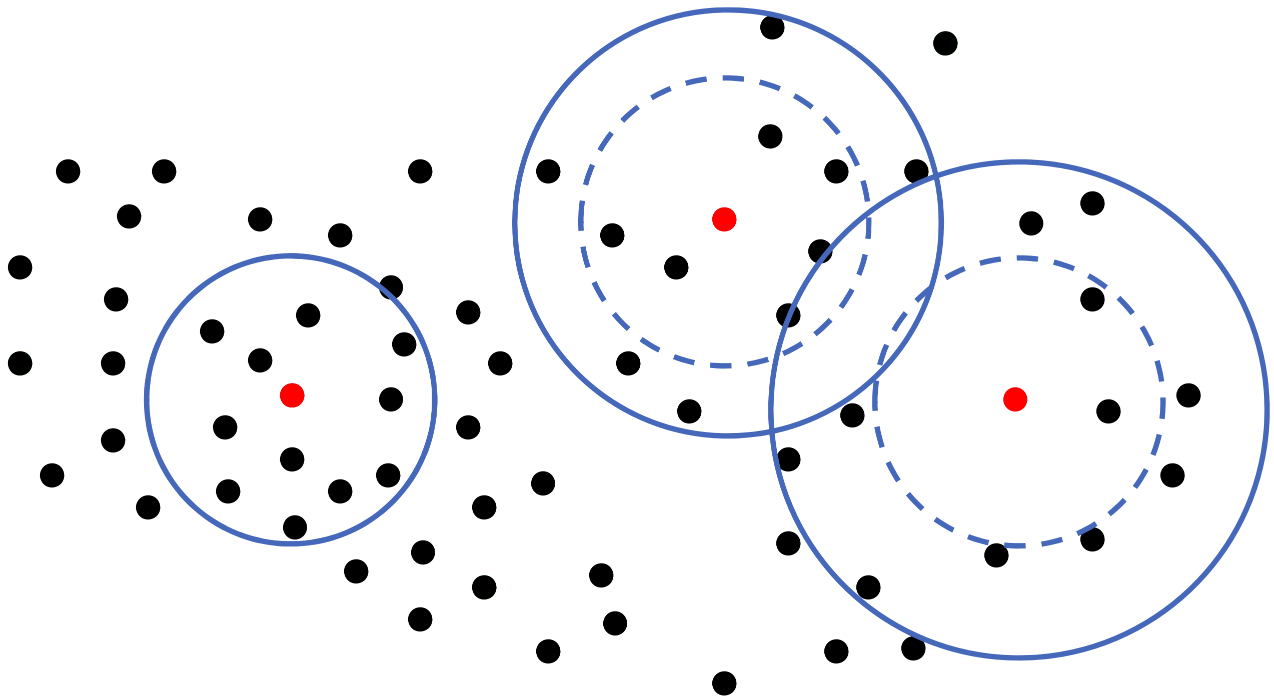


Objective: Processing laser datasets with large variation in point density

LiDAR Data Characterization

- Local point density estimation: why?

Definition of meaningful neighborhoods of irregularly-spaced LiDAR points for reliable data processing activities

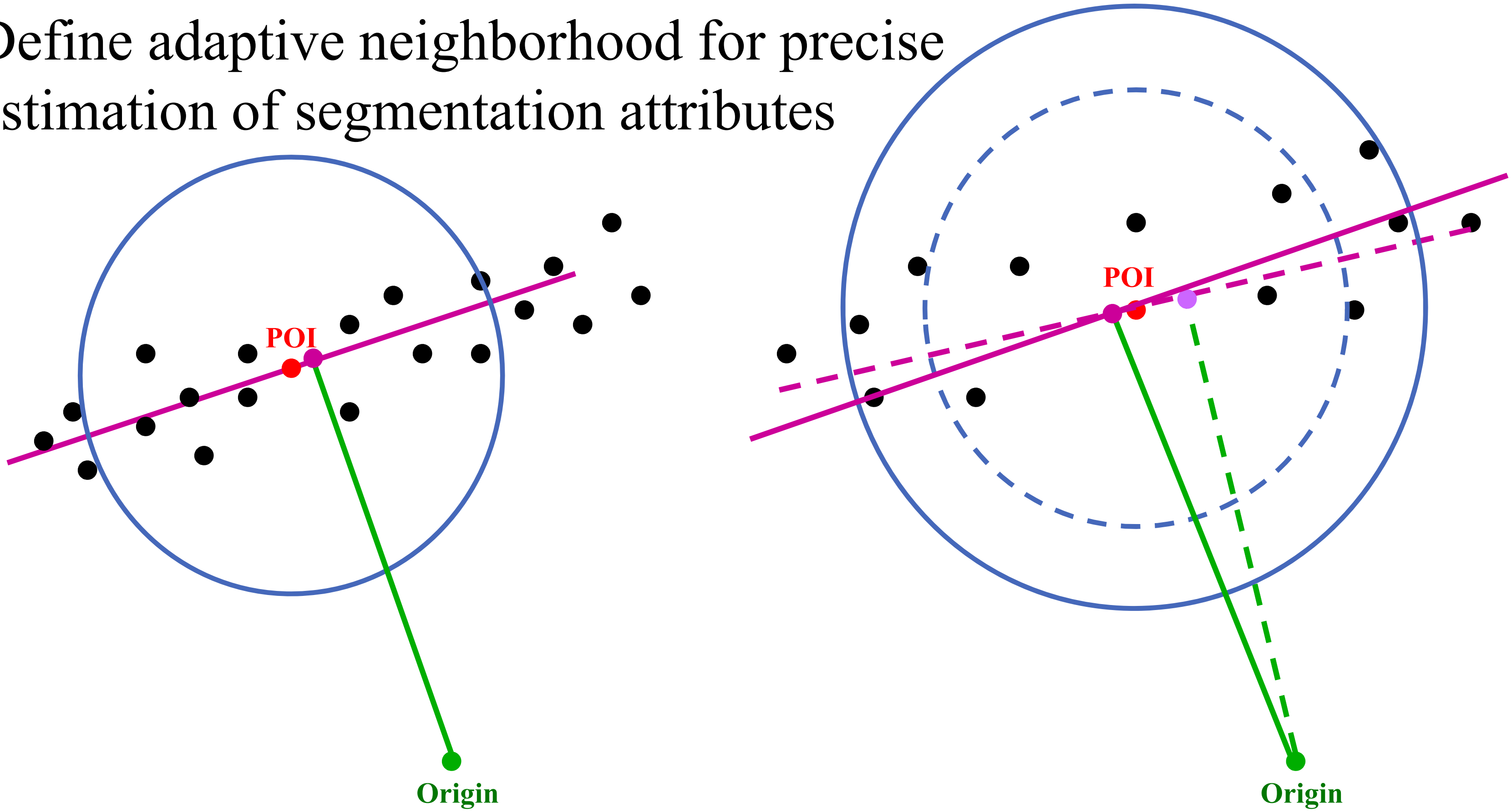


LiDAR Data Characterization

- Local point density estimation: why?

Adaptive processing of LiDAR Data

Define adaptive neighborhood for precise estimation of segmentation attributes

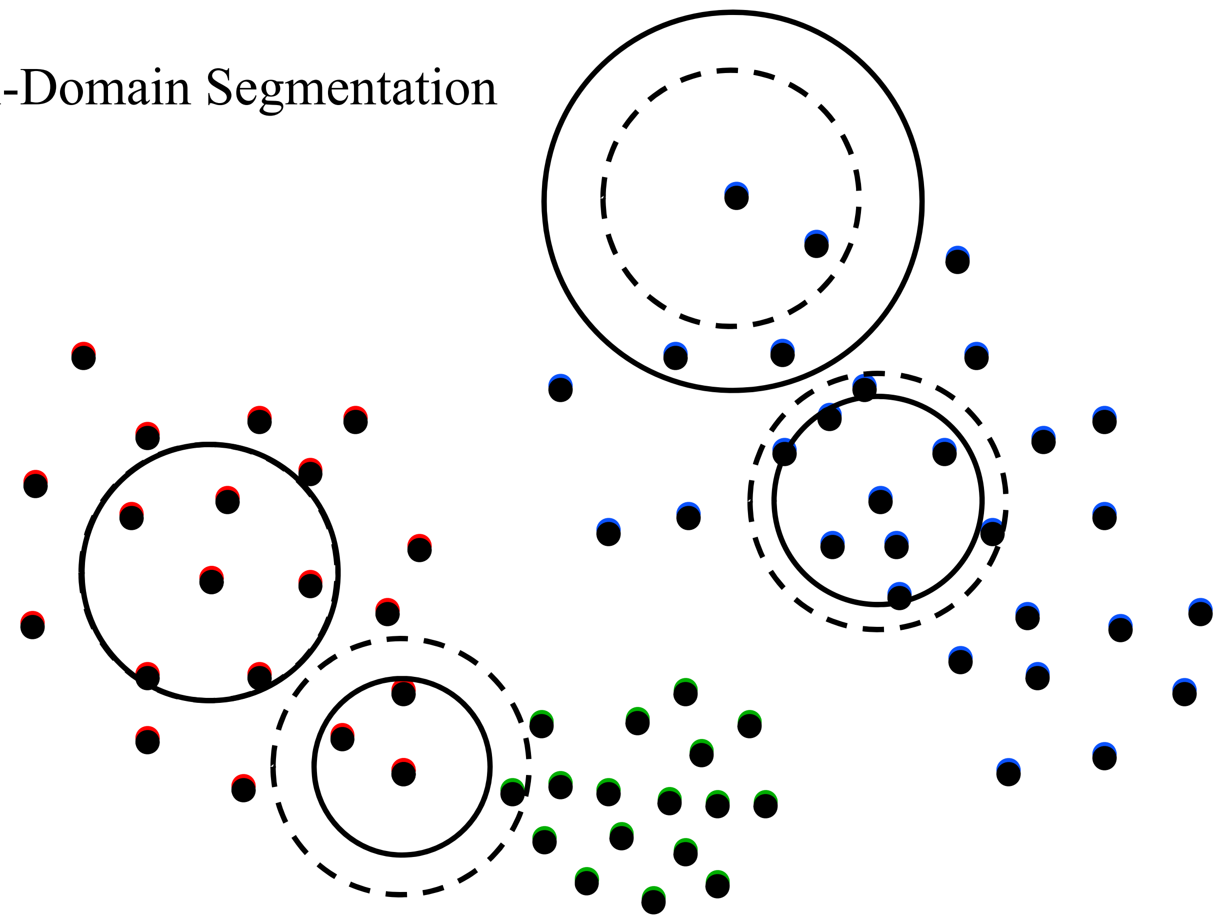


LiDAR Data Characterization

- Local point density estimation: why?

Adaptive processing of LiDAR Data

Spatial-Domain Segmentation

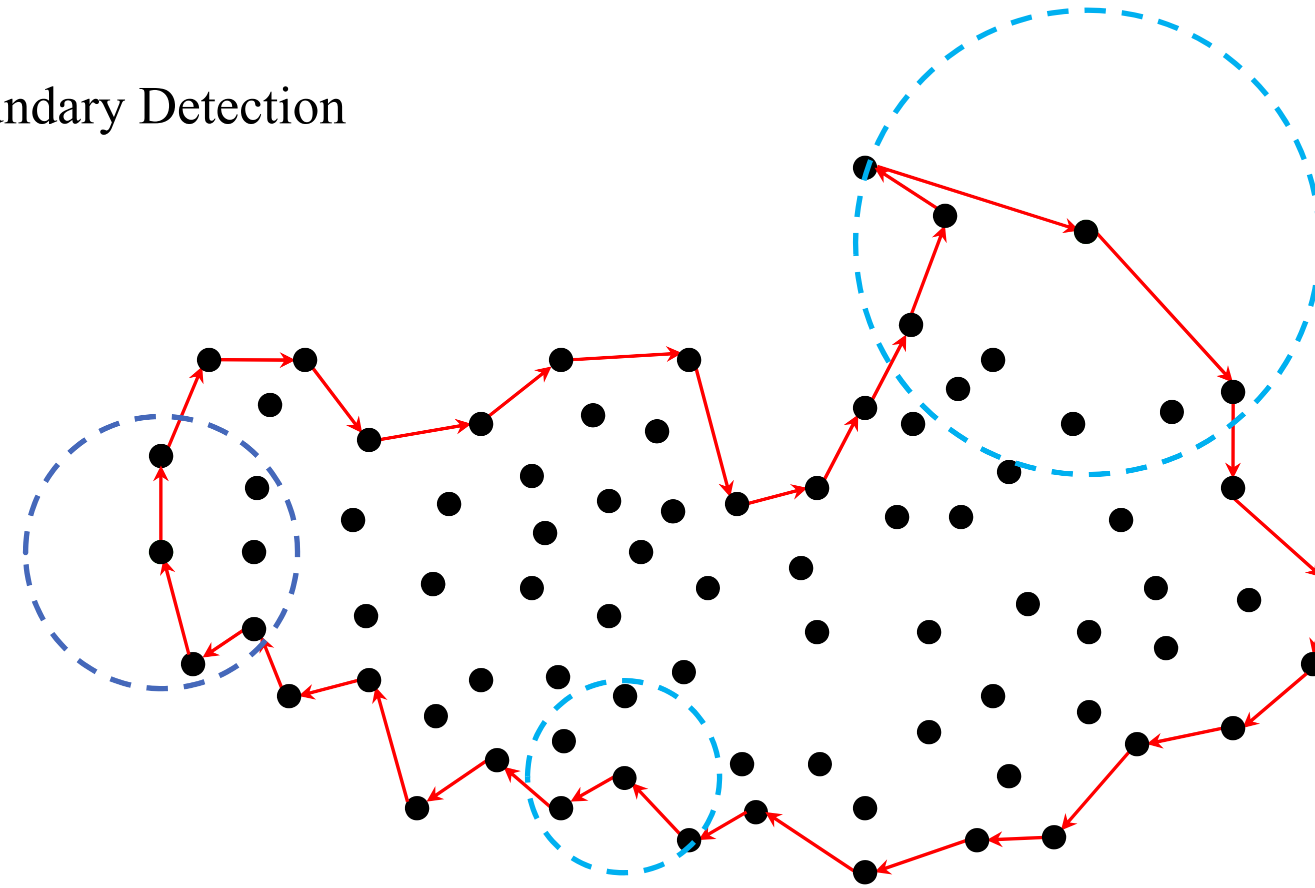


LiDAR Data Characterization

- Local point density estimation: why?

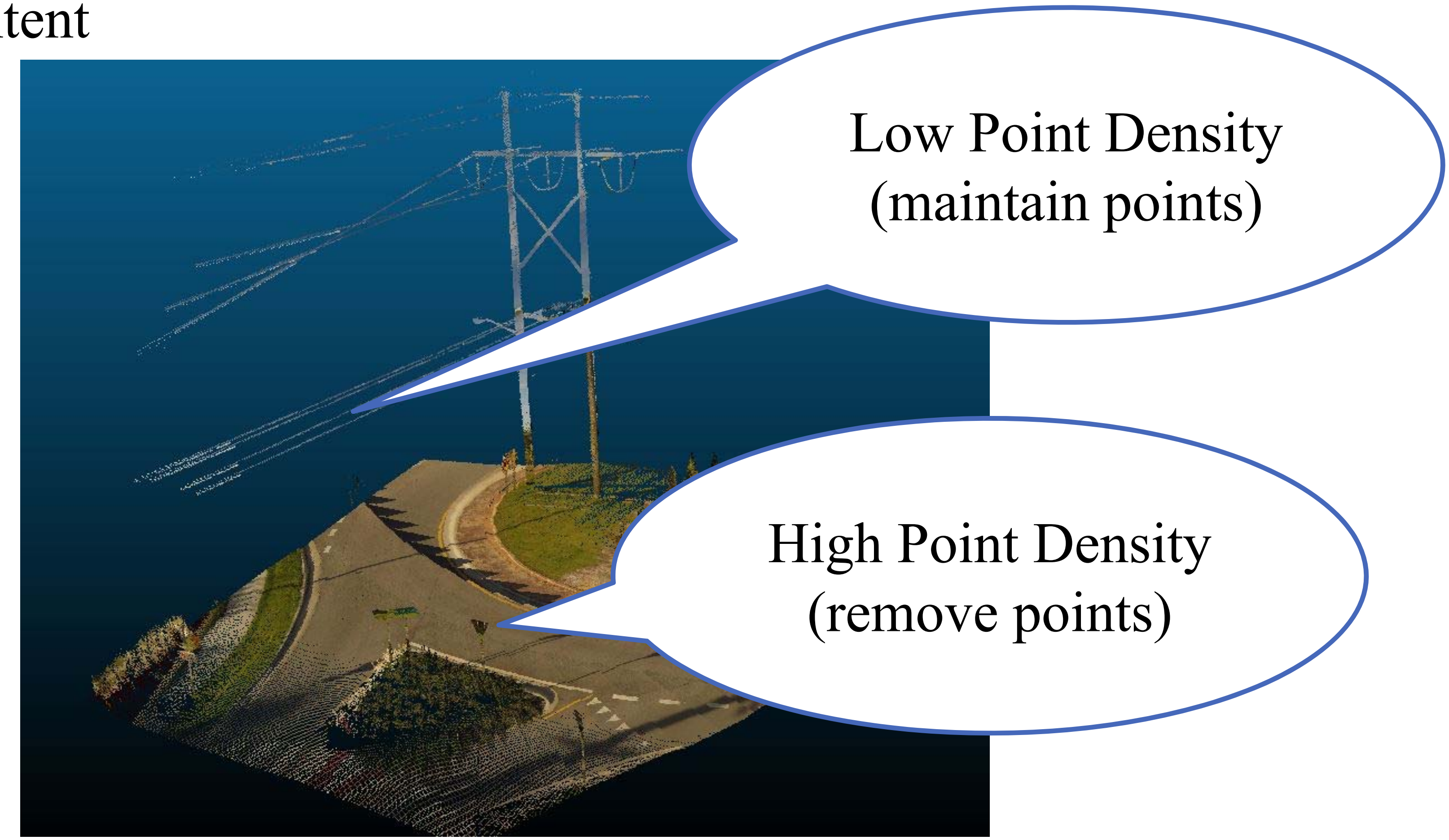
Adaptive processing of LiDAR Data

Boundary Detection



LiDAR Data Characterization

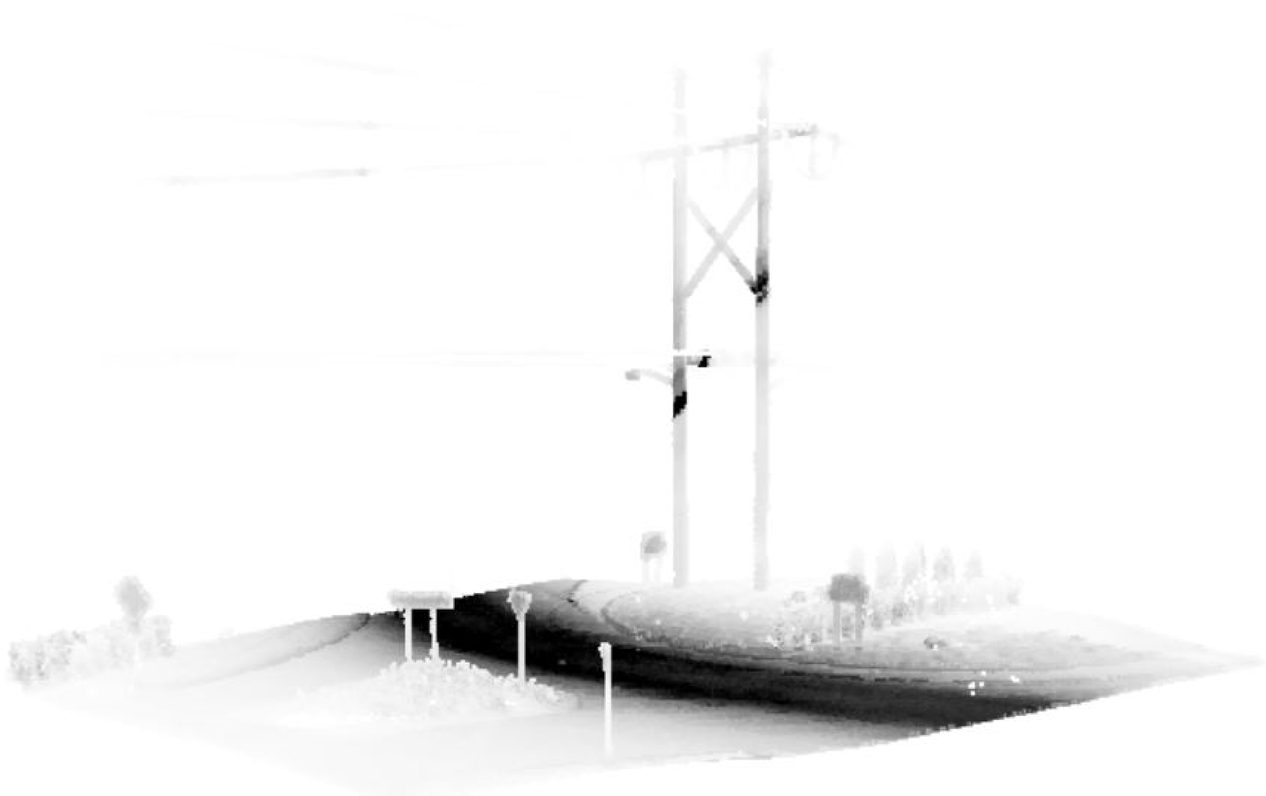
- Local point density estimation: why?
  - LiDAR Data Down Sampling while maintaining the information content



LiDAR Data Characterization

- Local point density estimation: why?
  - LiDAR Data Down Sampling while maintaining the information content

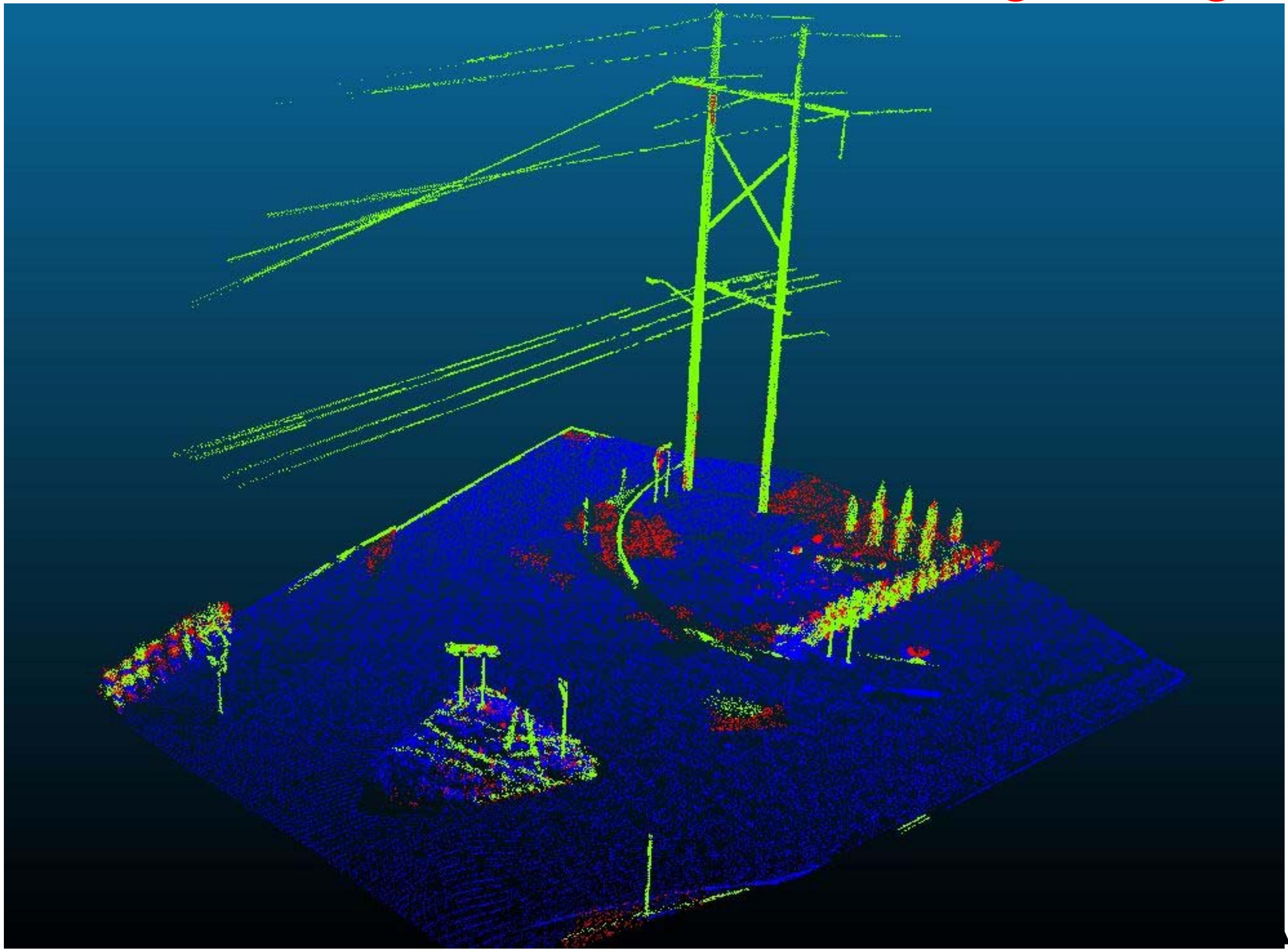
Original Data



LiDAR Data Characterization

- Local point density estimation: why?
  - LiDAR Data Down Sampling while maintaining the information content

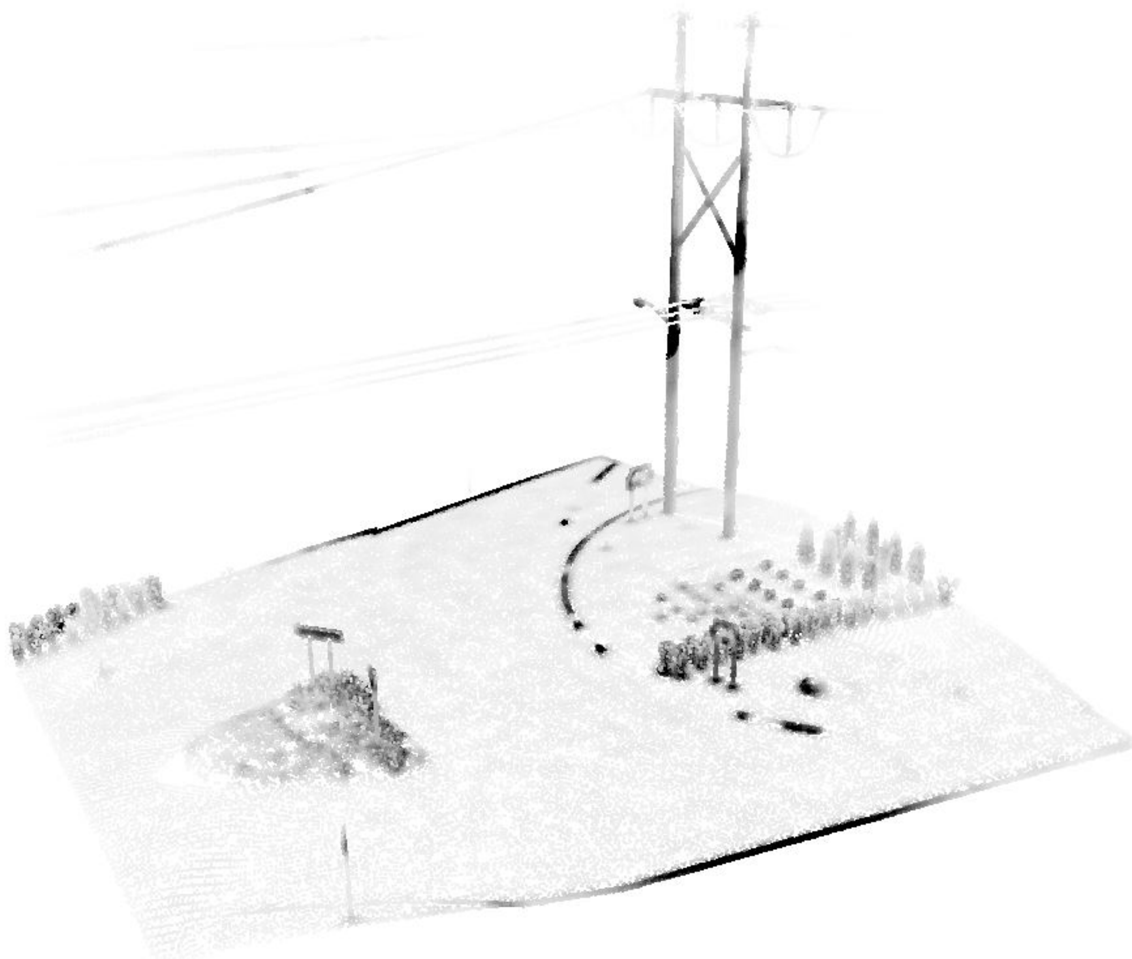
Original Segmented Data



LiDAR Data Characterization

- Local point density estimation: why?
  - LiDAR Data Down Sampling while maintaining the information content

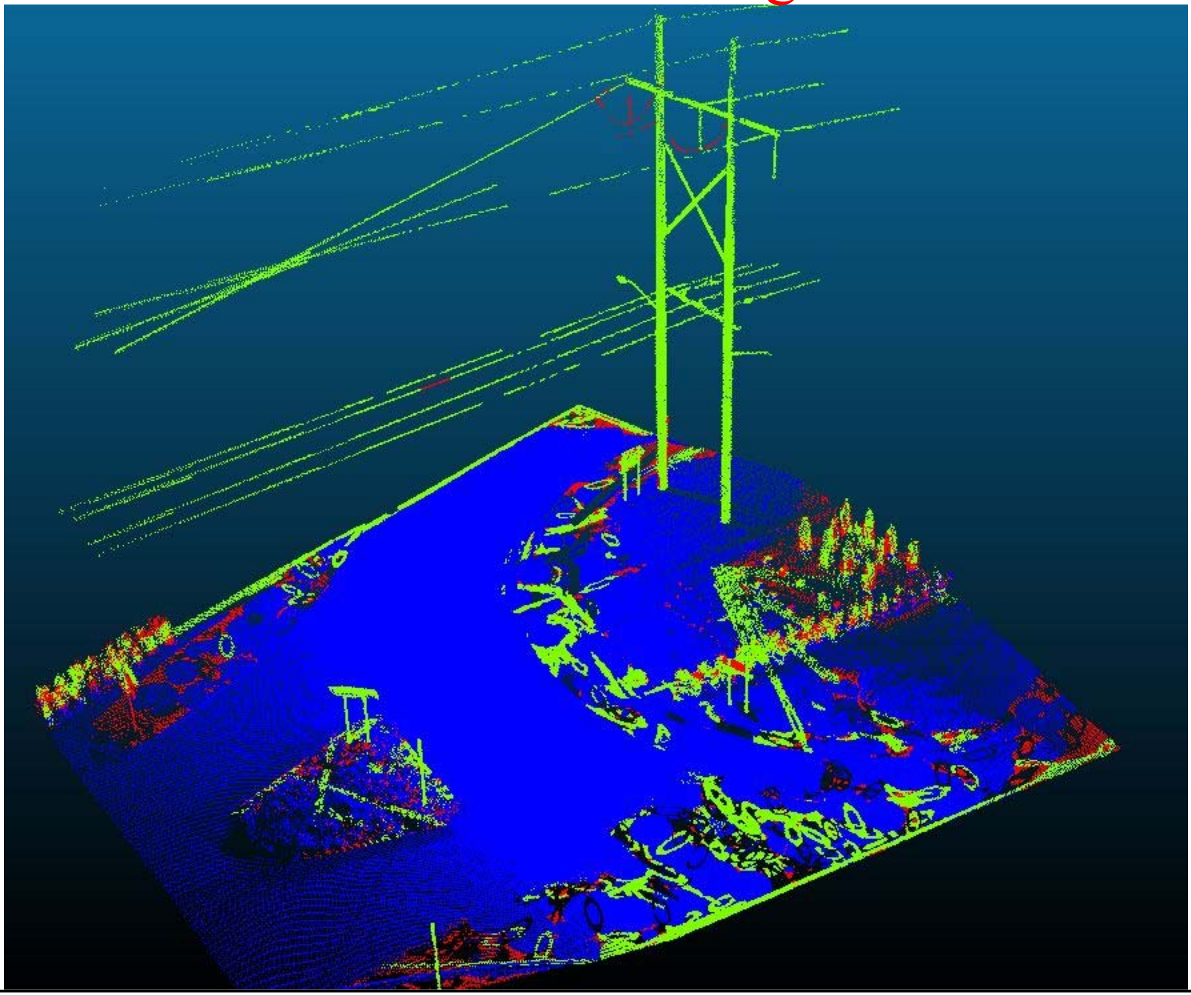
Down-sampled Data



LiDAR Data Characterization

- Local point density estimation: why?
  - LiDAR Data Down Sampling while maintaining the information content

Segmented Down-sampled Data

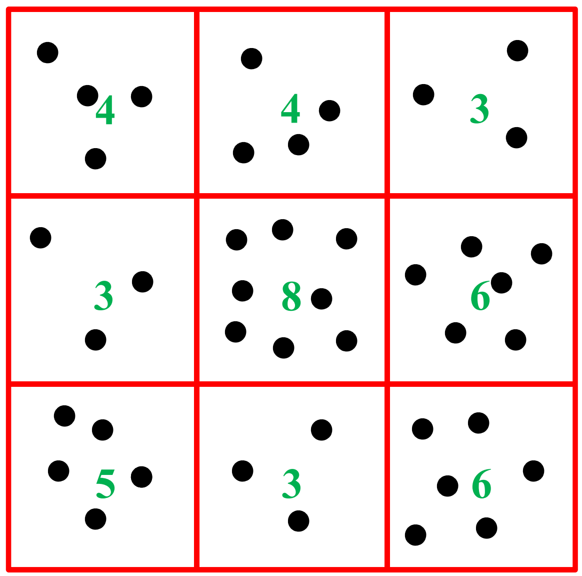


LiDAR Data Characterization

- **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: Existing Approaches

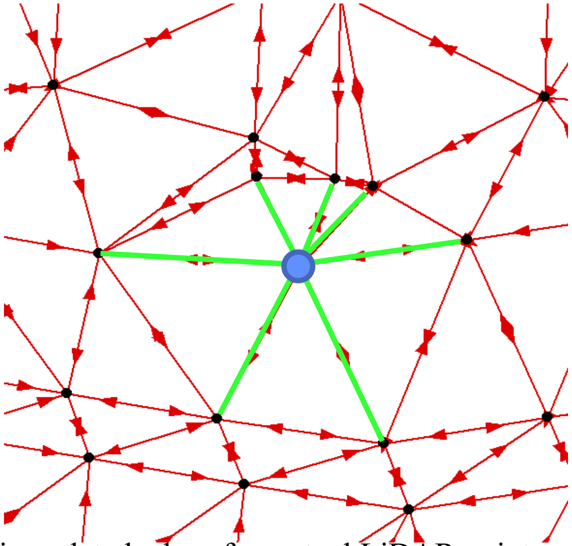
- **Box-counting method** (County, 2003): Derived the point density by a "box counting", where the area of the rectangle is associated with the total number of LiDAR points inside the rectangle.



  - 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: Existing Approaches

- **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

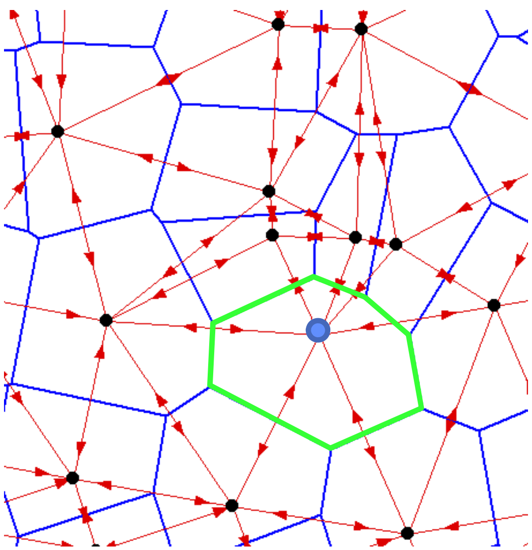


Delaunay triangulated edges for actual LiDAR points are shown in red.

Unbiased LiDAR Data Measurement, Ty Naus, Fugro Horizons, Inc

LPD Estimation: Existing Approaches

- **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



Unbiased LiDAR Data Measurement, Ty Naus, Fugro Horizons, Inc

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

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

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

LPD Estimation: Existing Approaches

- **Drawbacks of existing techniques:**
  - 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.

LPD Estimation: Proposed Approaches

- 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 two 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

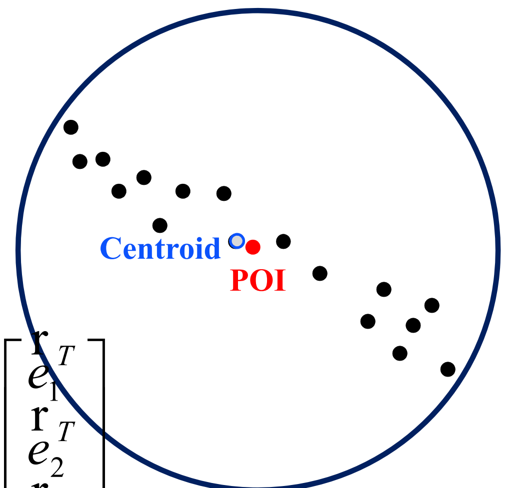
LPD Estimation: Proposed Approaches (1)

- **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

$$C_{3\times 3} = \frac{1}{n+1}\sum_{i=1}^{n+1}(\vec{r}_i - \vec{r}_{centroid})(\vec{r}_i - \vec{r}_{centroid})^T$$

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

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



  - Eigen value decomposition of the dispersion matrix

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

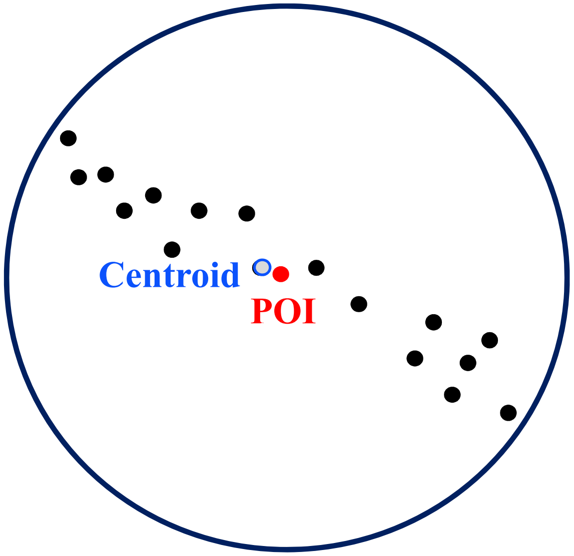
If $\lambda_1\ (\approx 0) \ll \lambda_2, \lambda_3$ the point of interest (POI) is considered to belong to a planar surface.

LPD Estimation: Proposed Approaches (1)

- **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:

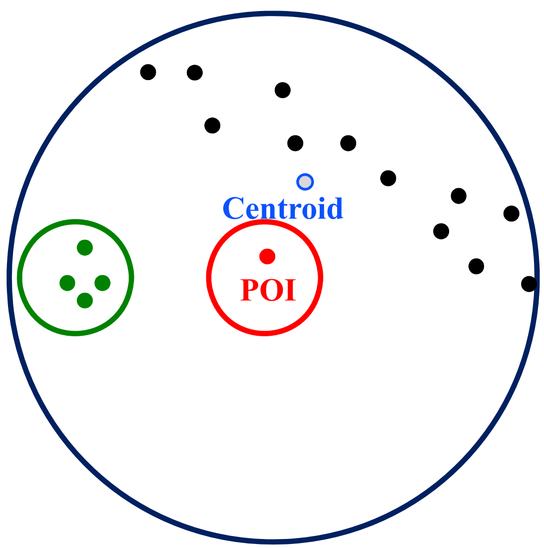
$$LPD = \frac{n+1}{\pi\, r_n^{\;2}}$$

n+1	Number of points within the spherical neighborhood
$\boldsymbol{r_n}$	The distance between the POI and its n^{th}-farthest neighbor



LPD Estimation: Proposed Approaches (1)

- **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



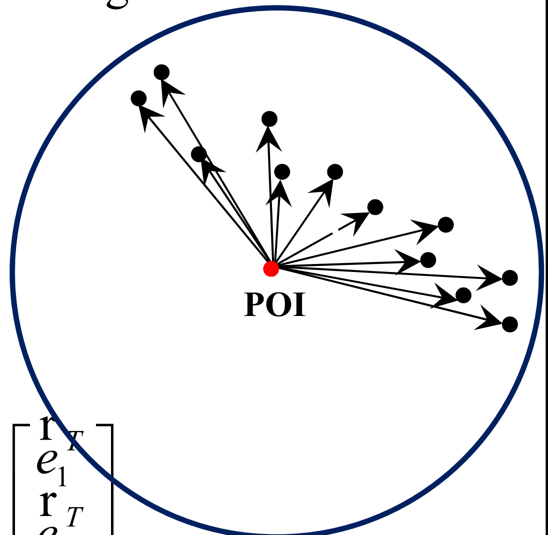
LPD Estimation: Proposed Approaches (2)

- **Classification using Eigen value analysis of the dispersion of 3D neighbouring points relative to the POI:**
  - Define a spherical neighbourhood 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 neighbourhood relative to the point of interest (POI)

$$C_{3\times 3} = \frac{1}{n}\sum_{i=1}^{n}(\vec{r}_i - \vec{r}_{POI})(\vec{r}_i - \vec{r}_{POI})^T$$

$$\vec{r}_i = \begin{bmatrix} X_i & Y_i & Z_i \end{bmatrix}^T$$

$$\vec{r}_{POI} = \begin{bmatrix} X_{POI} & Y_{POI} & Z_{POI} \end{bmatrix}^T$$



  - Eigen value decomposition of the dispersion matrix

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

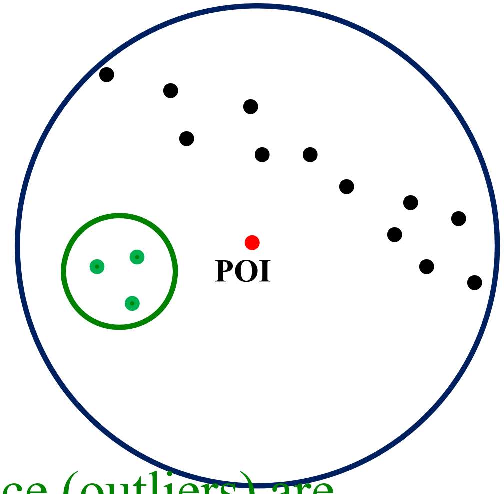
If $\lambda_1 (\approx 0) << \lambda_2, \lambda_3$, the point of interest (POI) is considered to belong to a planar surface.

LPD Estimation: Proposed Approaches (2)

- **Classification using Eigen value analysis of the dispersion of 3D neighbouring points relative to the POI:**

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

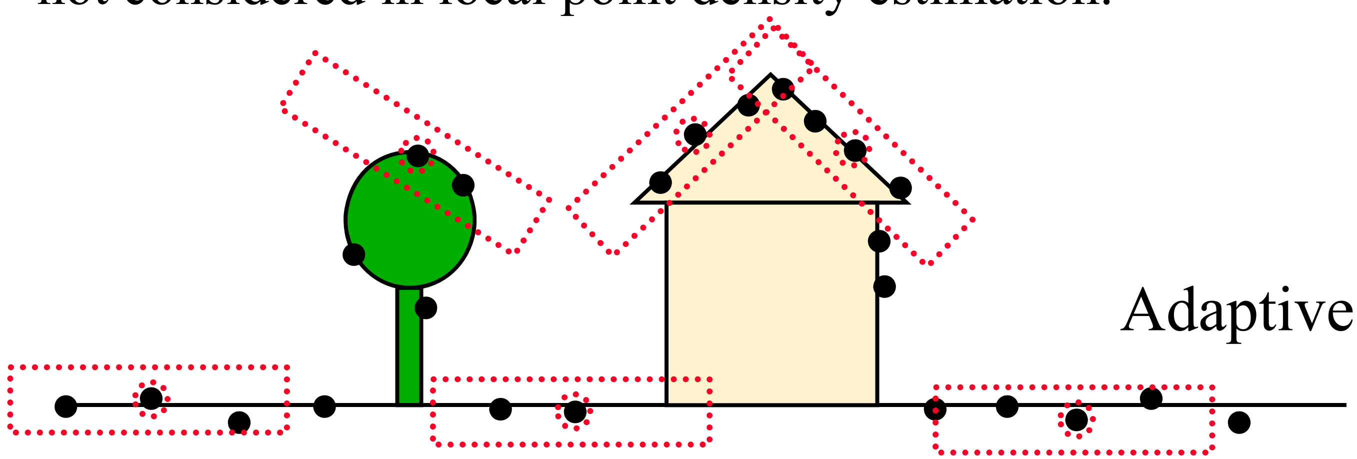
n+1	Number of the points within the spherical neighbourhood



- Disadvantages:
  - Points that do not belong to the local planar surface (outliers) are considered in LPD estimation

LPD Estimation: Proposed Approaches (3)

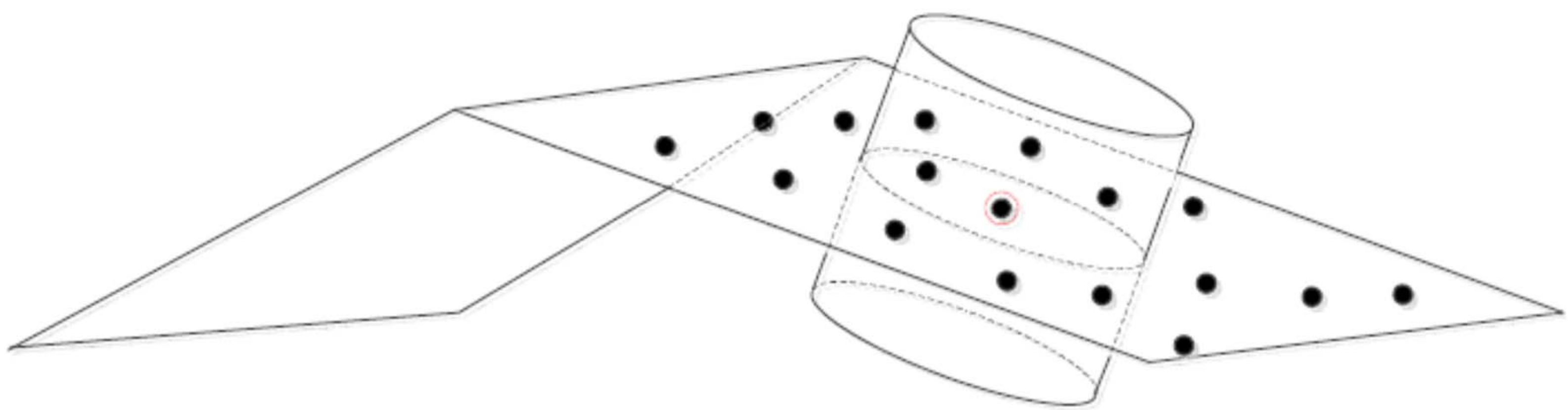
- **Classification using an adaptive cylinder:**
  - This approach is based on defining a cylinder, which changes its orientation with the local planar surface. This cylinder is used to decide whether the point belongs to a planar or rough surface.
- Advantages:
  - ➢ Takes into consideration whether 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.



Adaptive Cylinder

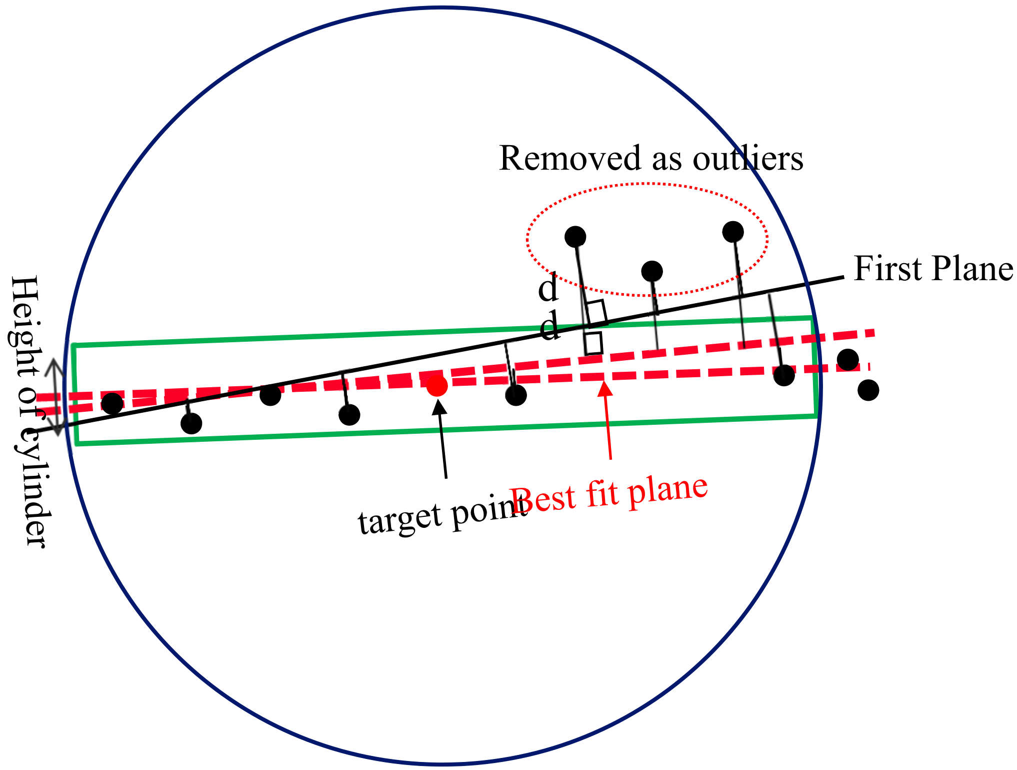
LPD Estimation: Proposed Approaches (3)

- **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.



LPD Estimation: Proposed Approaches (3)

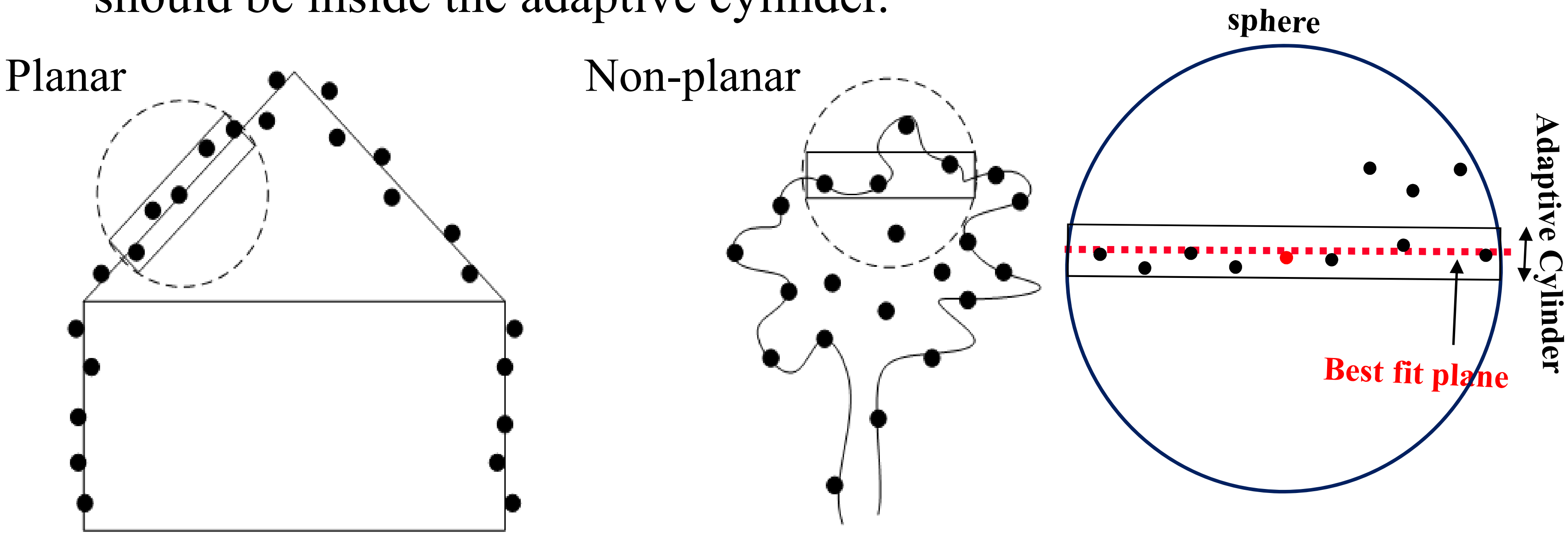
Derivation of the Adaptive Cylinder



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

LPD Estimation: Proposed Approaches (3)

- **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.

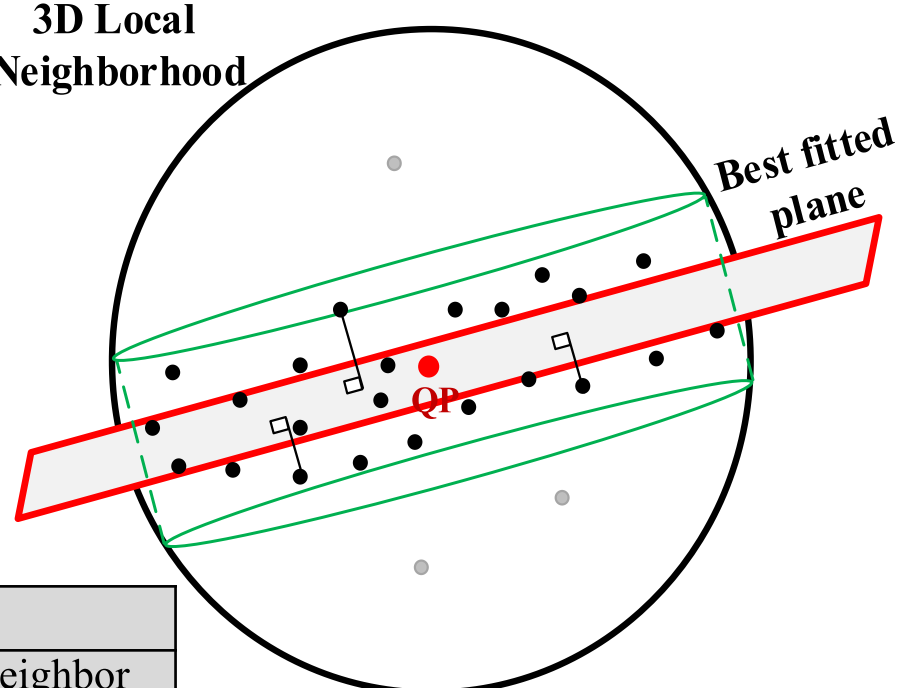


Occupancy Rate: 100%   Occupancy Rate: 60%

LPD Estimation: Proposed Approaches (3)

- **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 n[th]-farthest neighbor

k (number of pnts in adaptive cylinder) ≤ n (number of pnts in sphere)

LPD Estimation: Proposed Approaches

- **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.

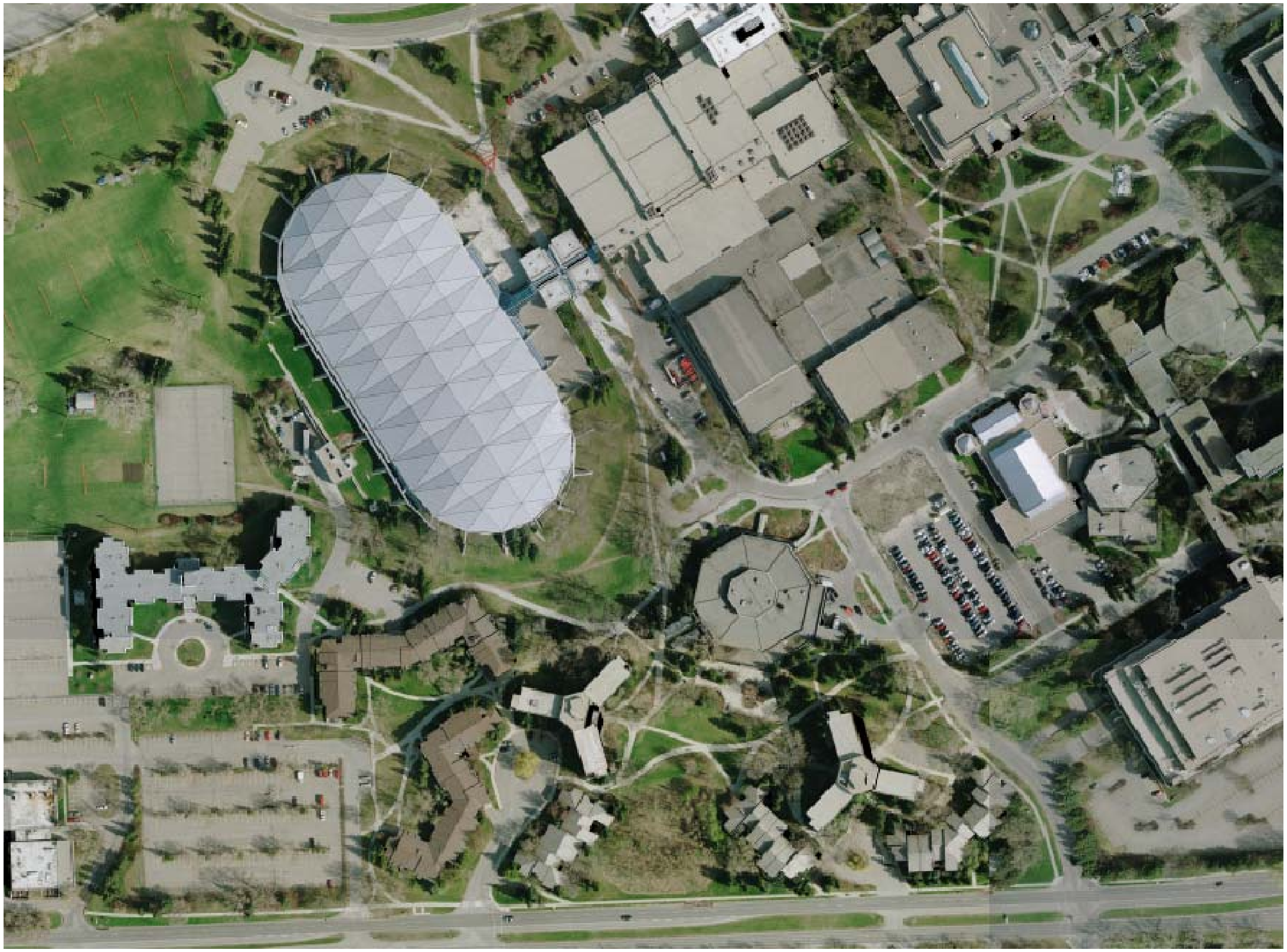
Experimental Results (Airborne Data – 1)

- Location: University of Calgary campus
- Average point density: 1 pnts/m^2

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%

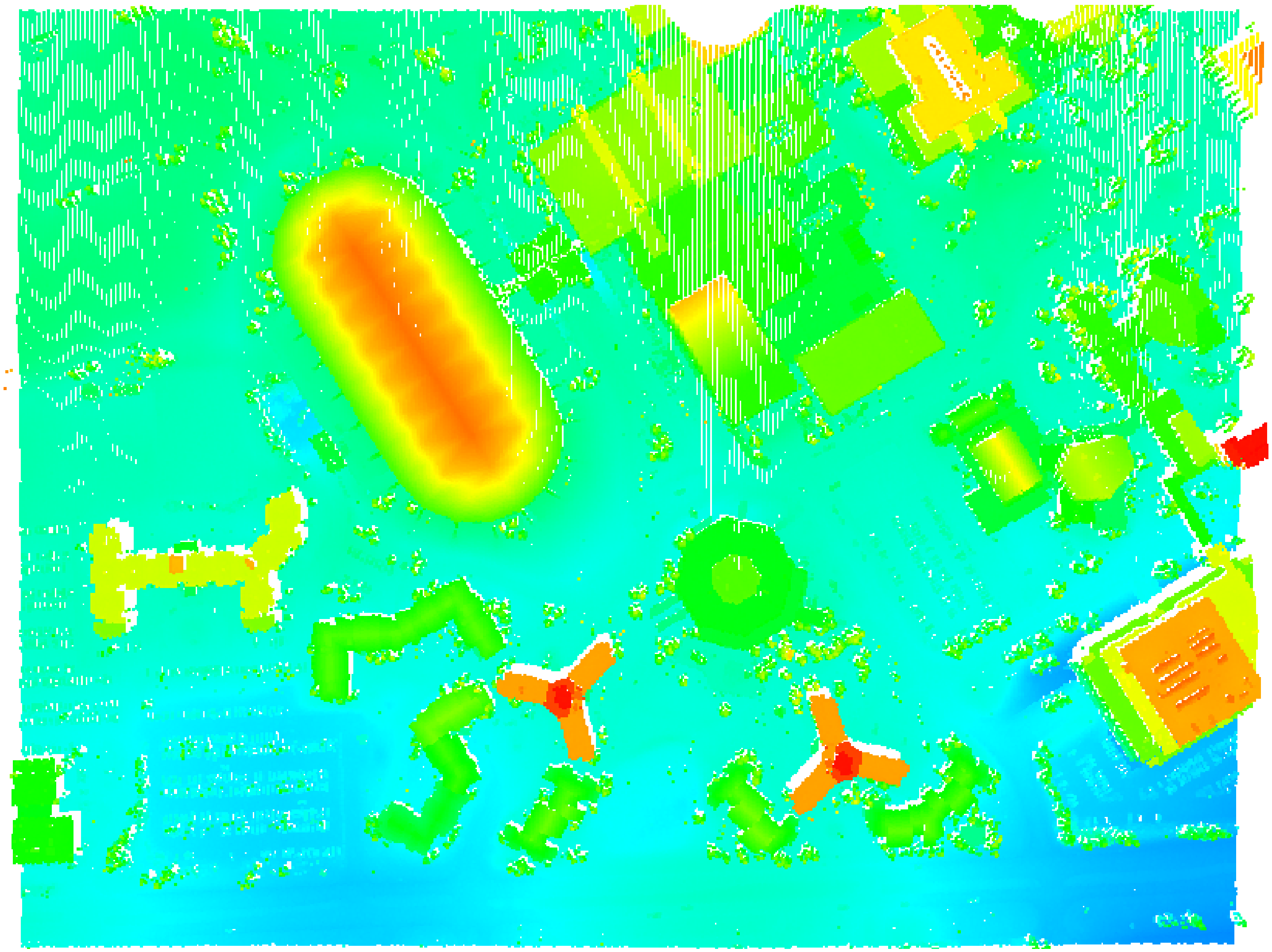
Experimental Results (Airborne Data – 1)

- Orthophoto over the test area:



Experimental Results (Airborne Data – 1)

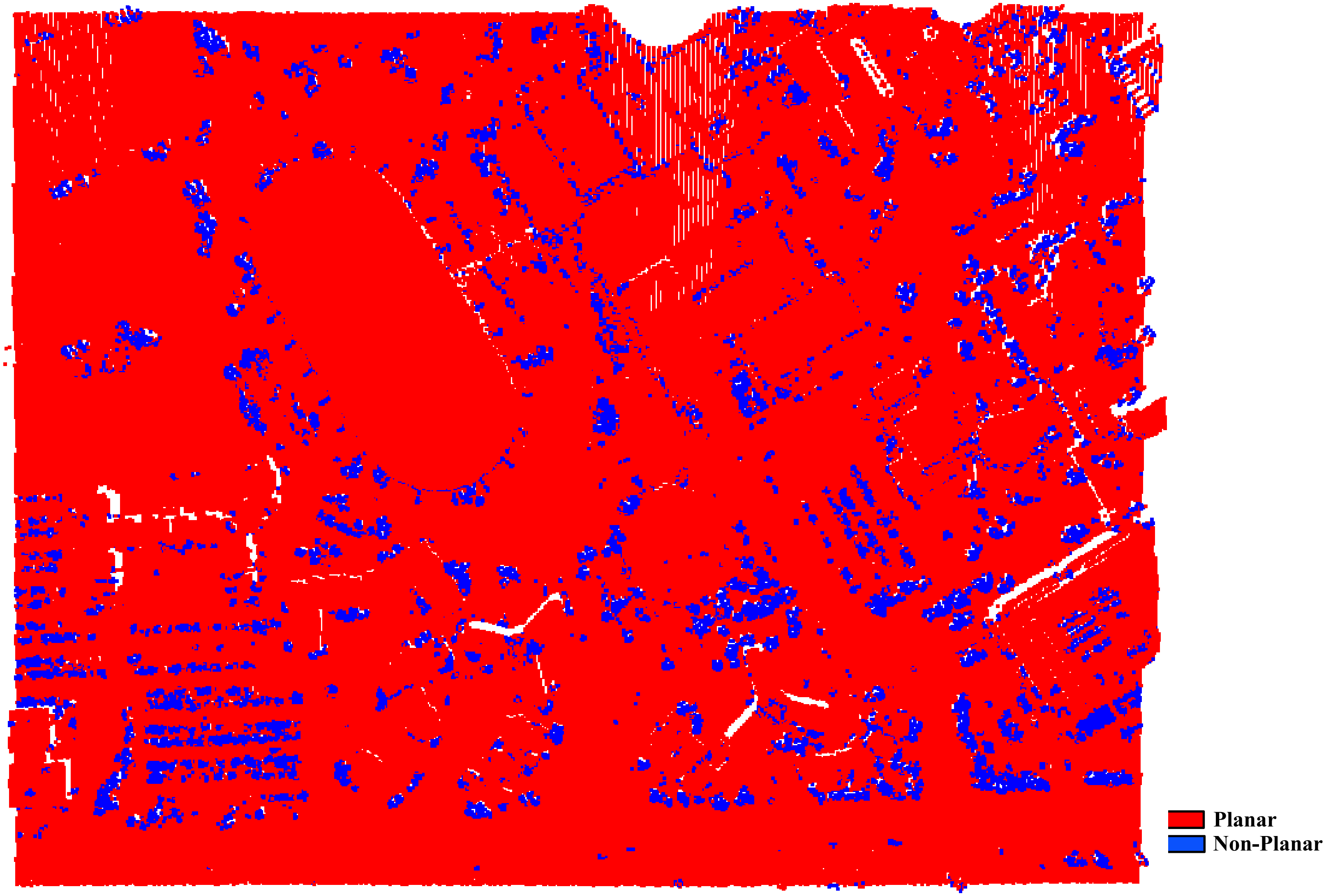
- Original LiDAR data:



Experimental Results (Airborne Data – 1)

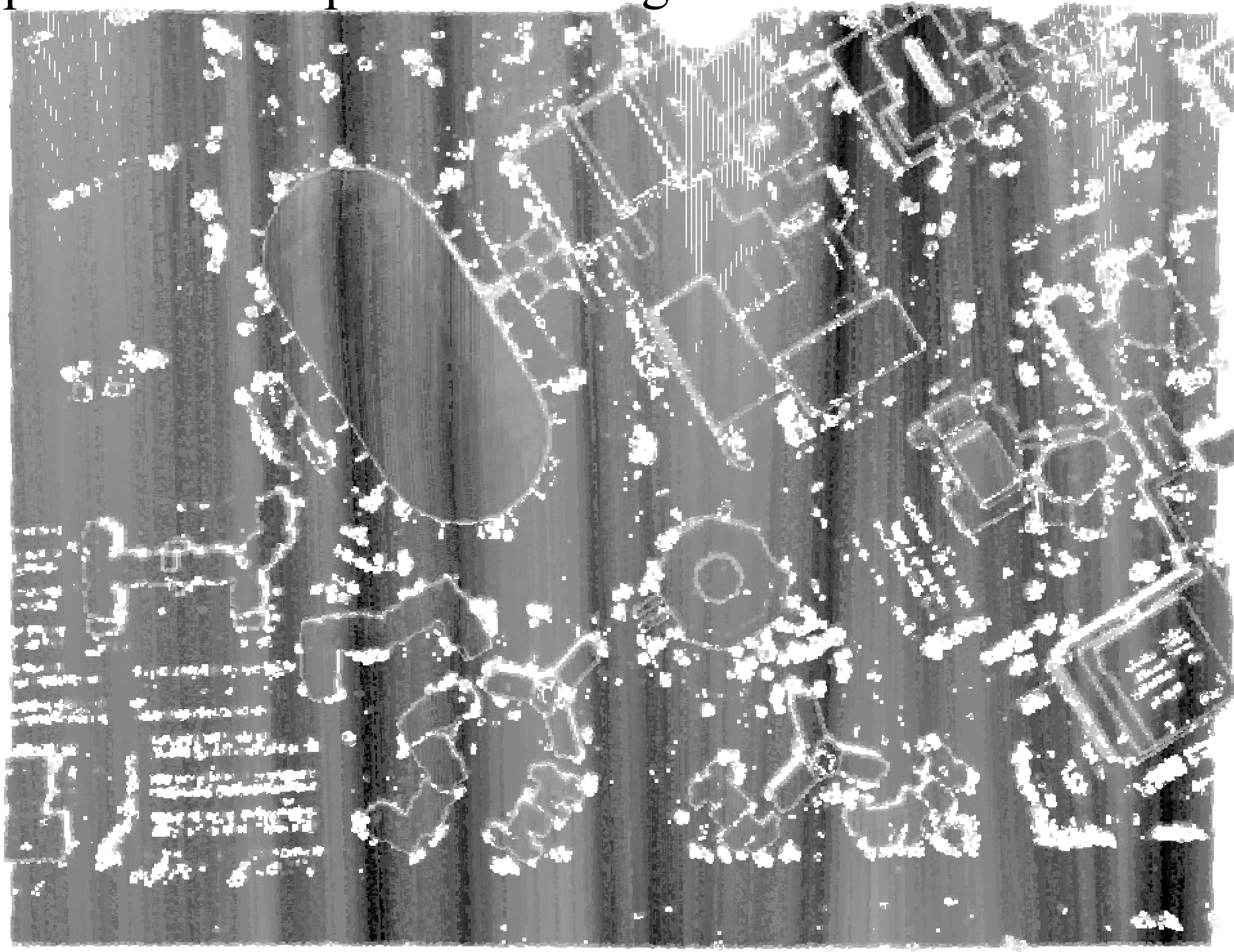
- Dispersion of the point's 3D neighbors relative to their centroid:

Classification Results



Experimental Results (Airborne Data – 1)

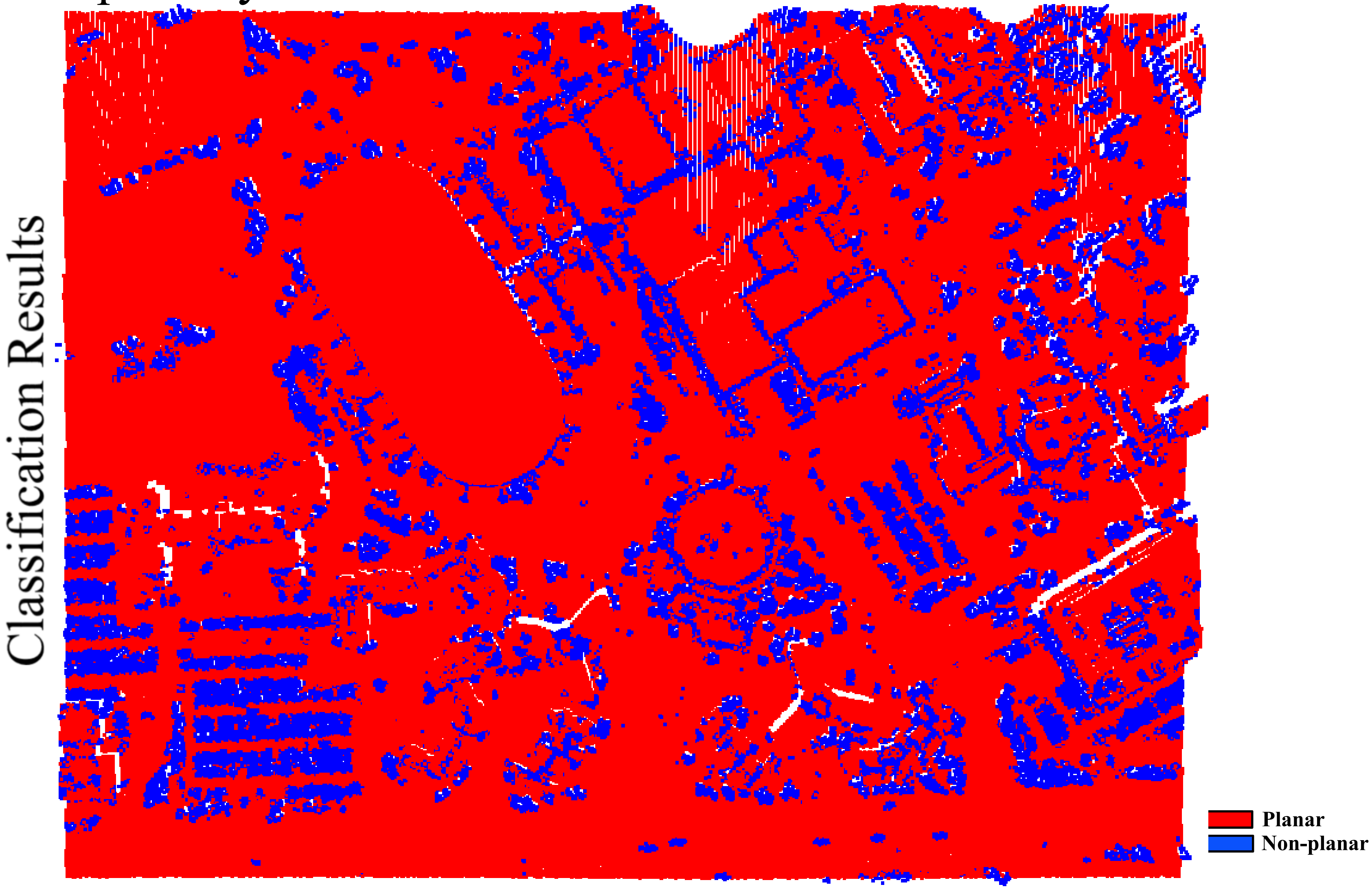
- Dispersion of the point's 3D neighbors relative to their centroid:



0 2.10

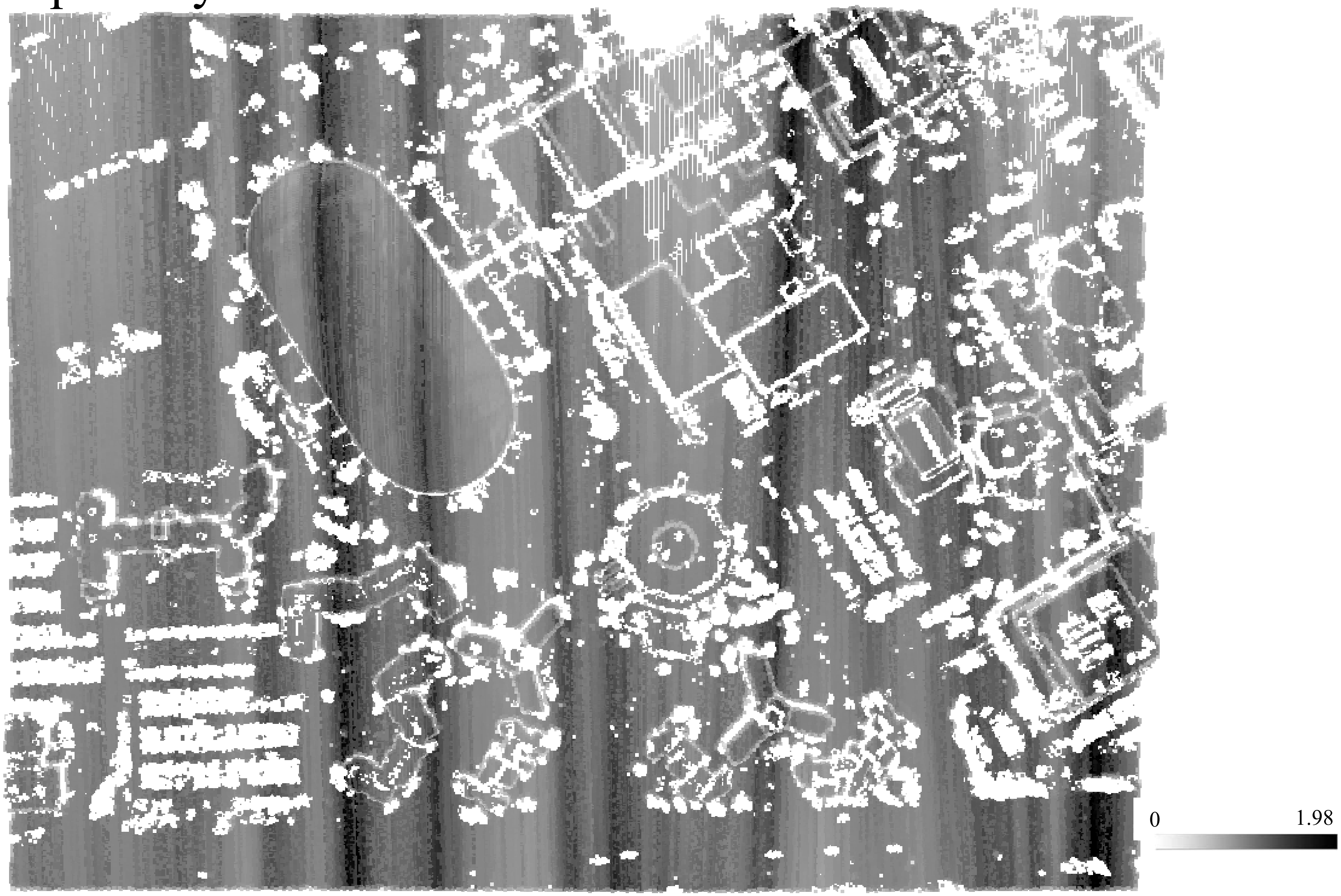
Experimental Results (Airborne Data – 1)

- Adaptive cylinder:



Experimental Results (Airborne Data – 1)

- Adaptive cylinder:



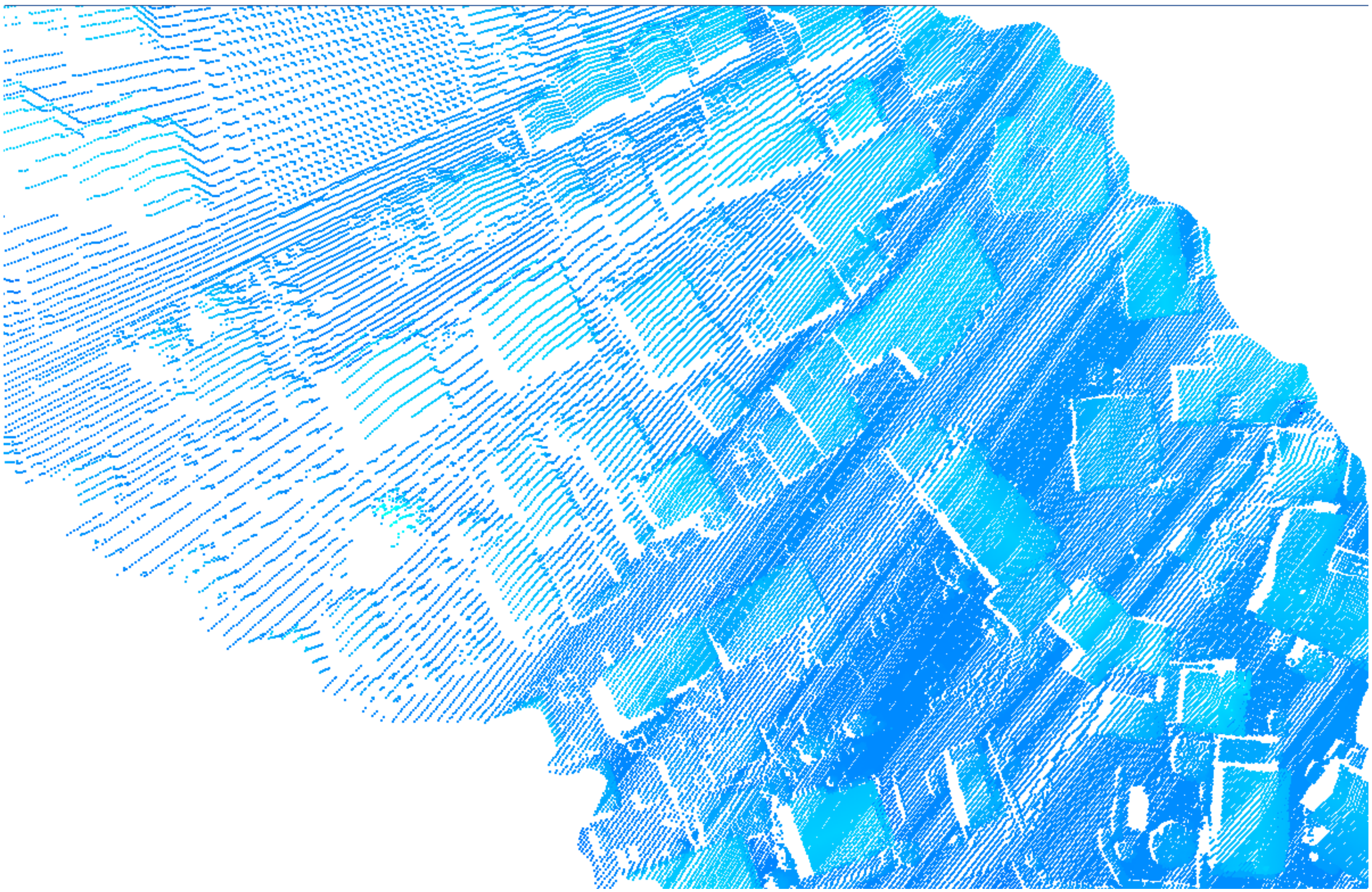
Experimental Results (Airborne Data – 2)

- Location: Switzerland
- Mean point density: 7 pnts/m^2

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%

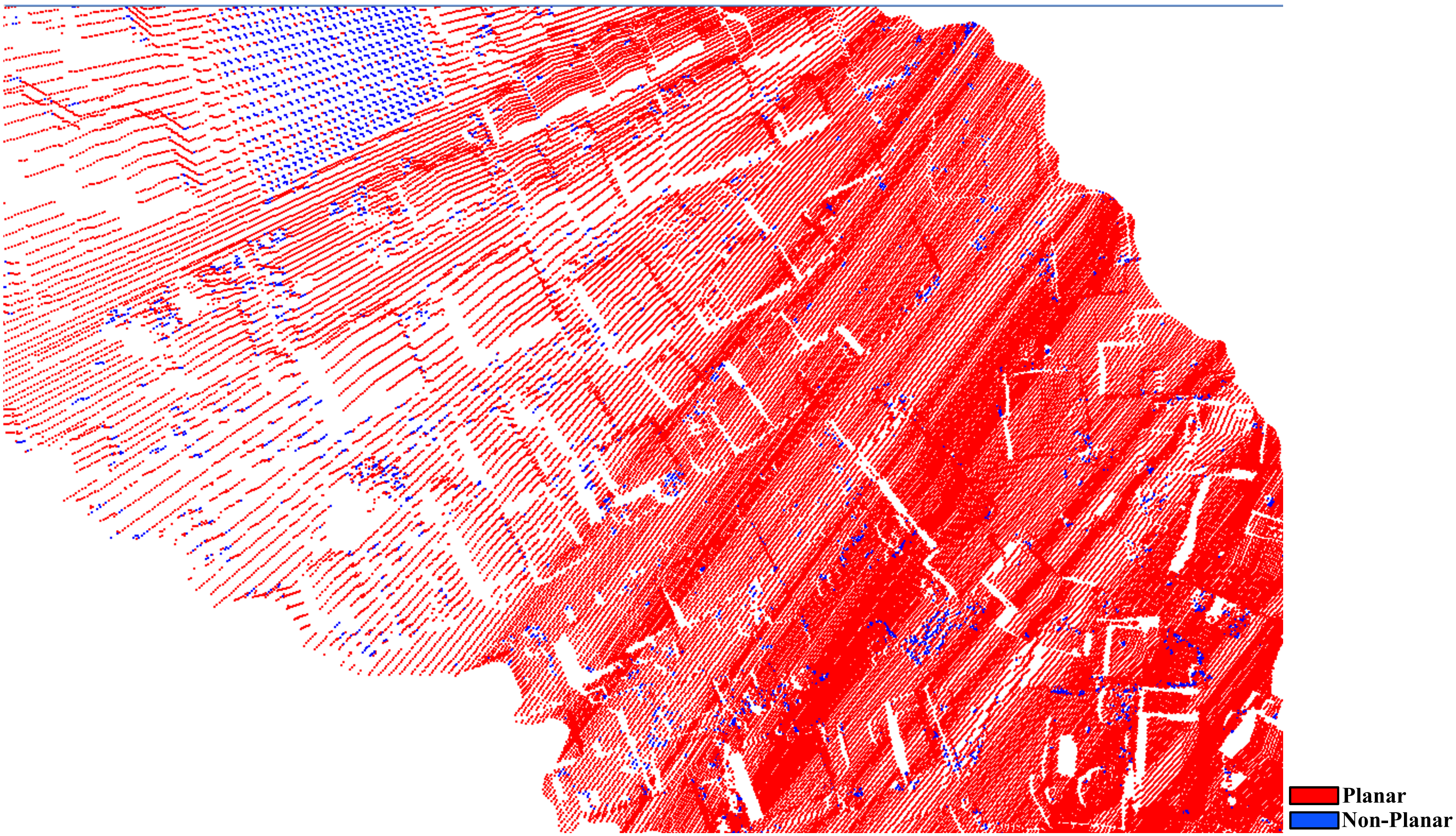
Experimental Results (Airborne Data – 2)

- Original LiDAR data:



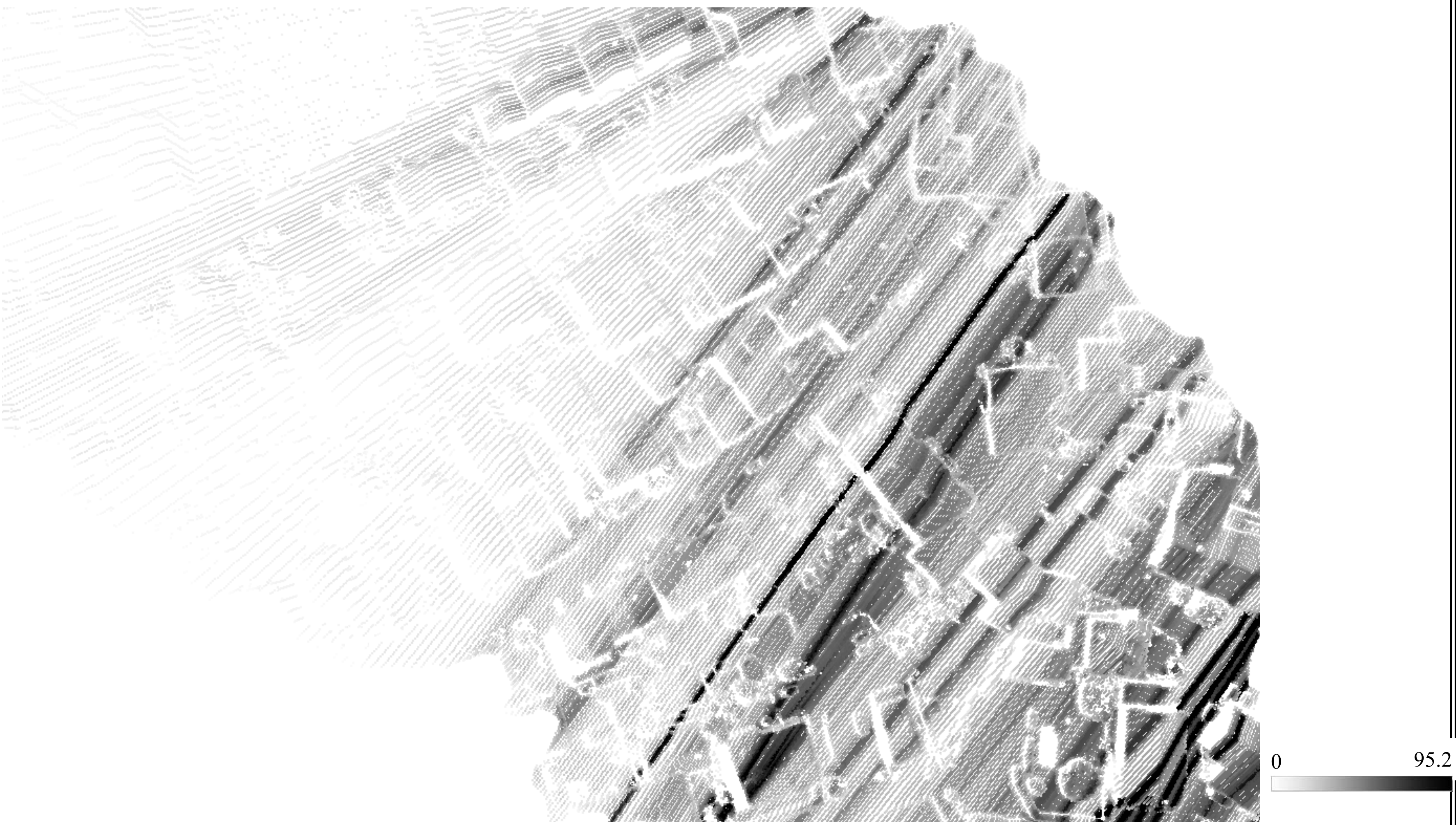
Experimental Results (Airborne Data – 2)

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



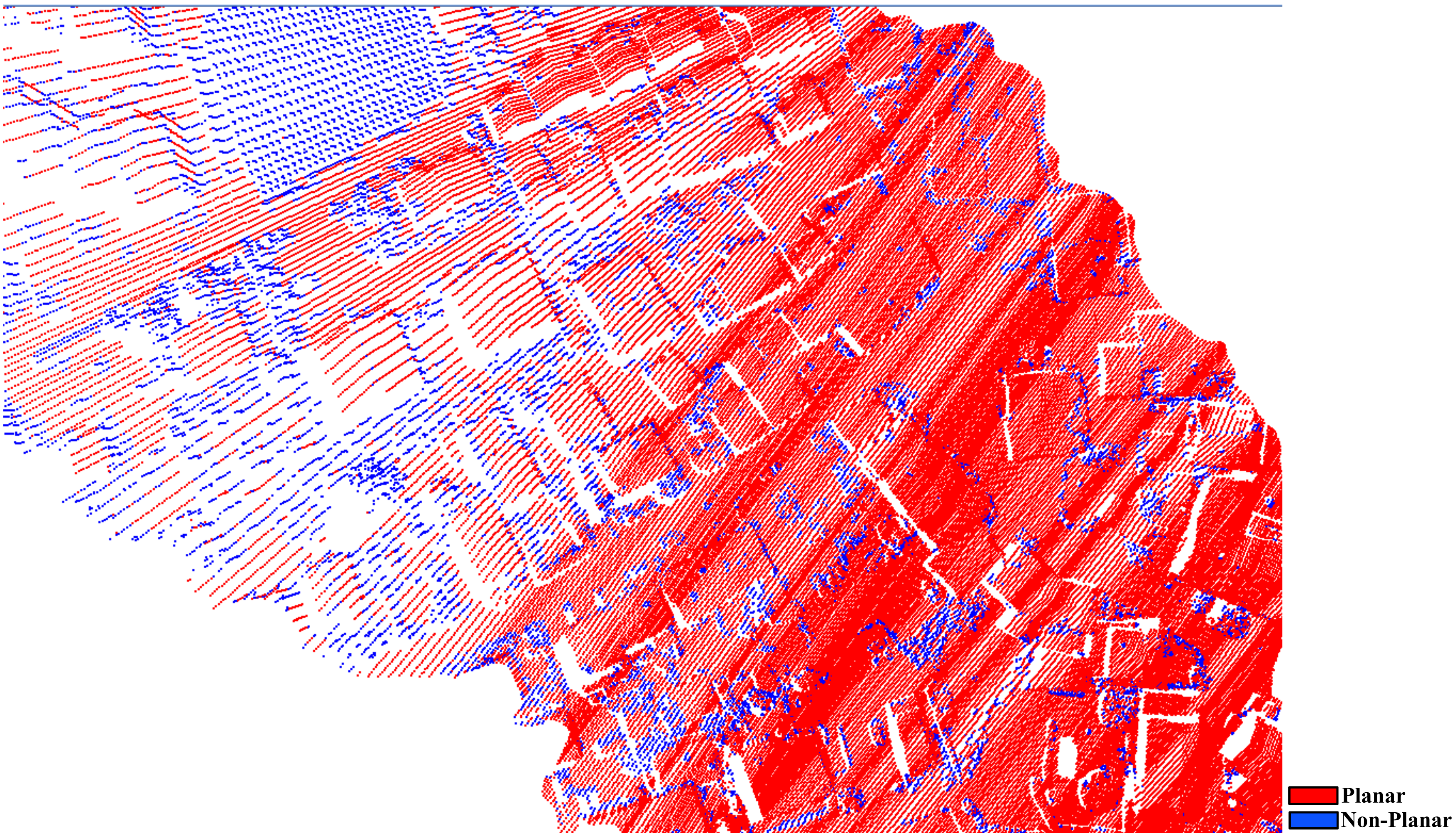
Experimental Results (Airborne Data – 2)

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



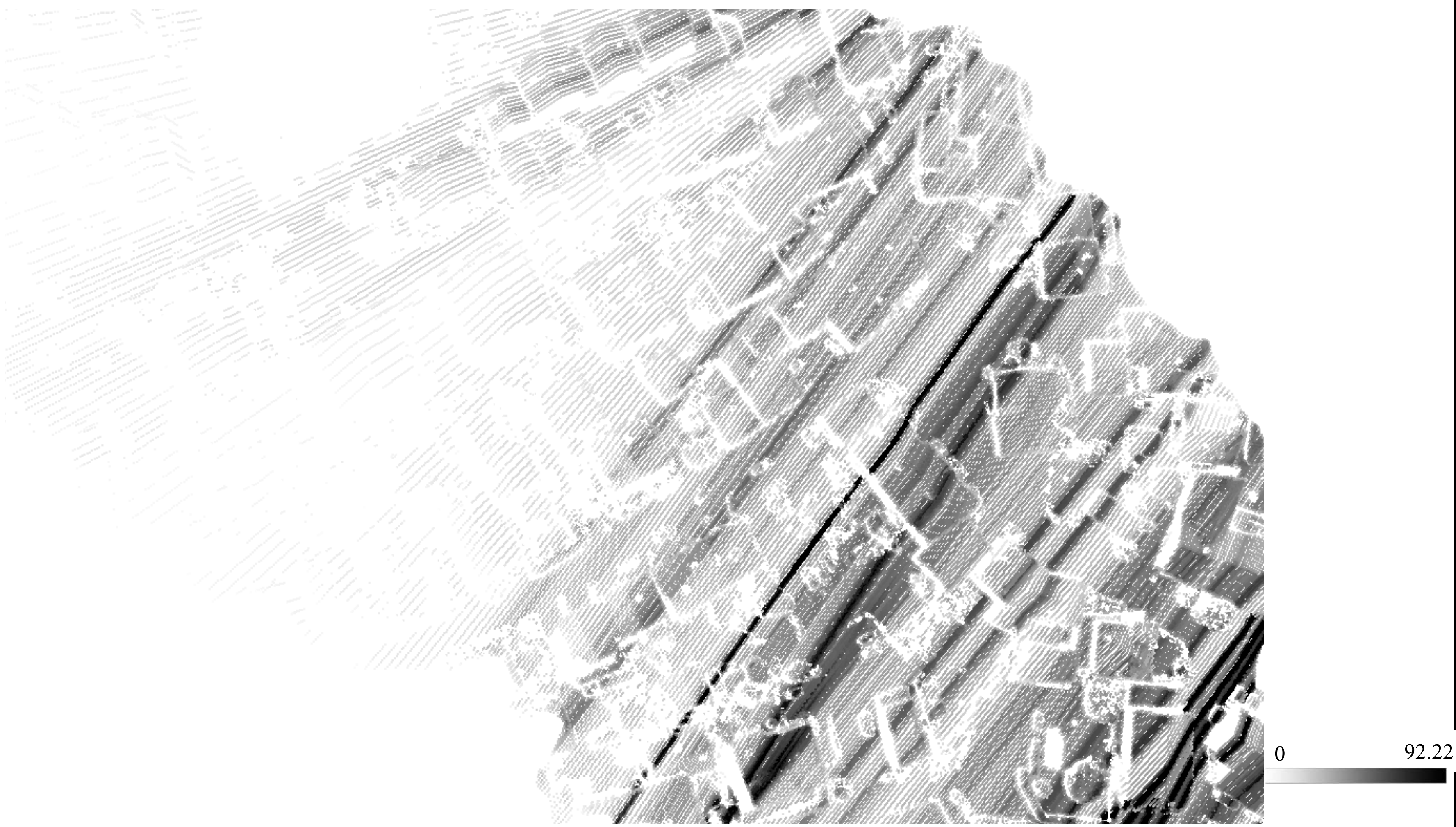
Experimental Results (Airborne Data – 2)

- Adaptive cylinder:



Experimental Results (Airborne Data – 2)

- Adaptive cylinder:



Experimental Results (Terrestrial Data)

- Location: Rozsa Center, University of Calgary
- Mean point density: 4218 pnts/m^2

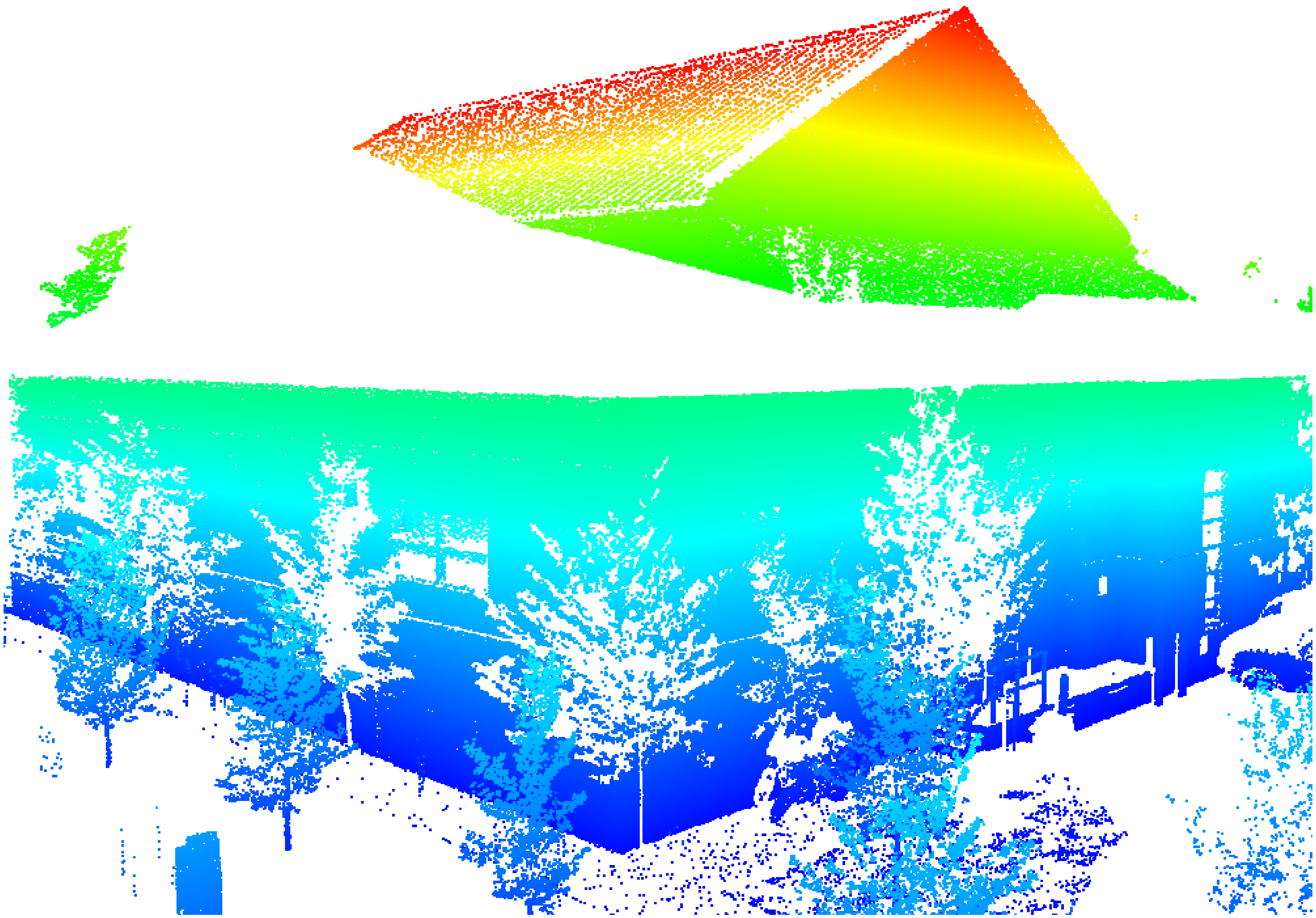
Threshold	Value
No. of neighboring points for Eigen-values calculation	25
No. of neighboring points for best fit plane definition	25
Height of cylinder	0.04 m
Planarity ratio	95%

Experimental Results (Terrestrial Data)

- Digital image:

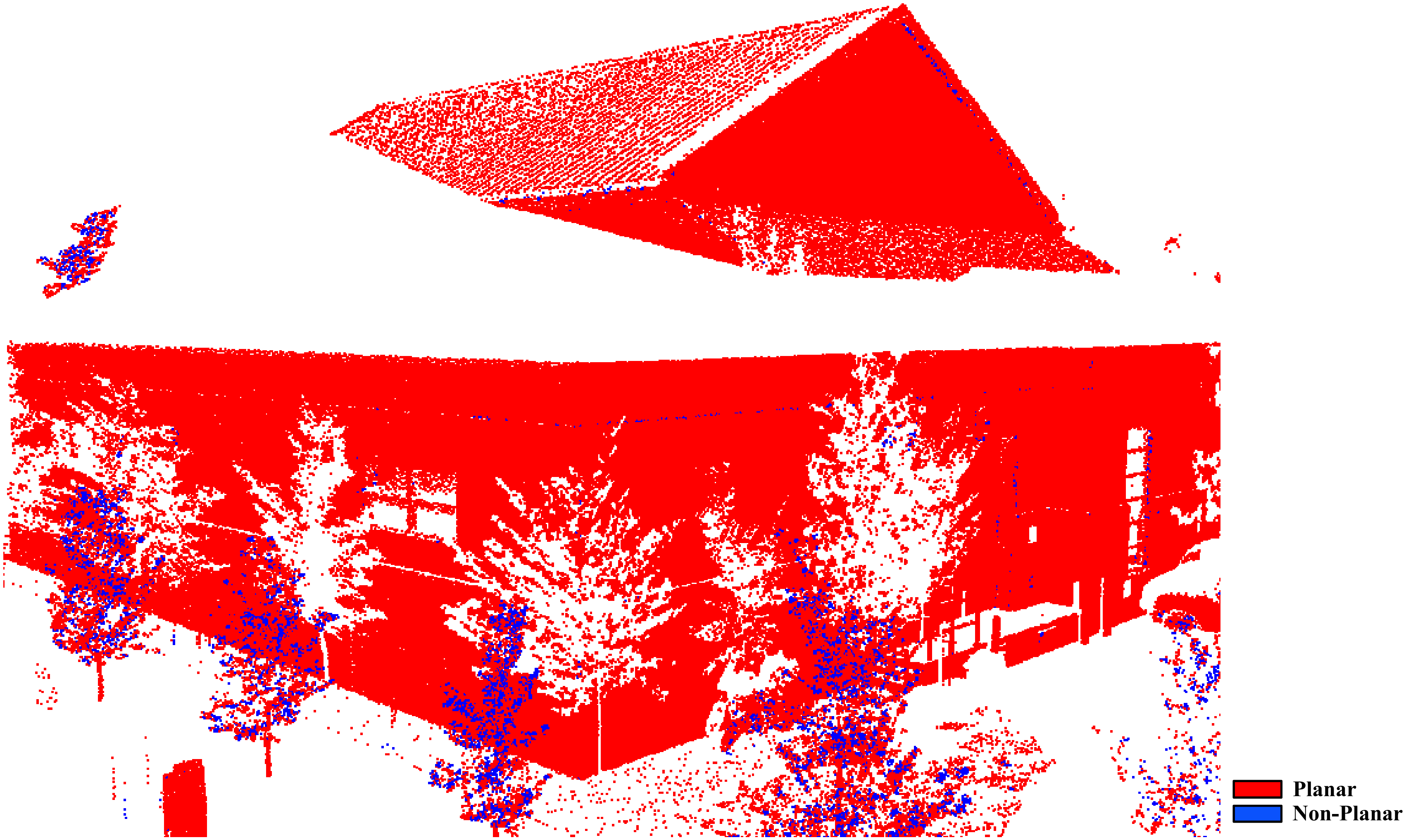
Experimental Results (Terrestrial Data)

- Original LiDAR data:



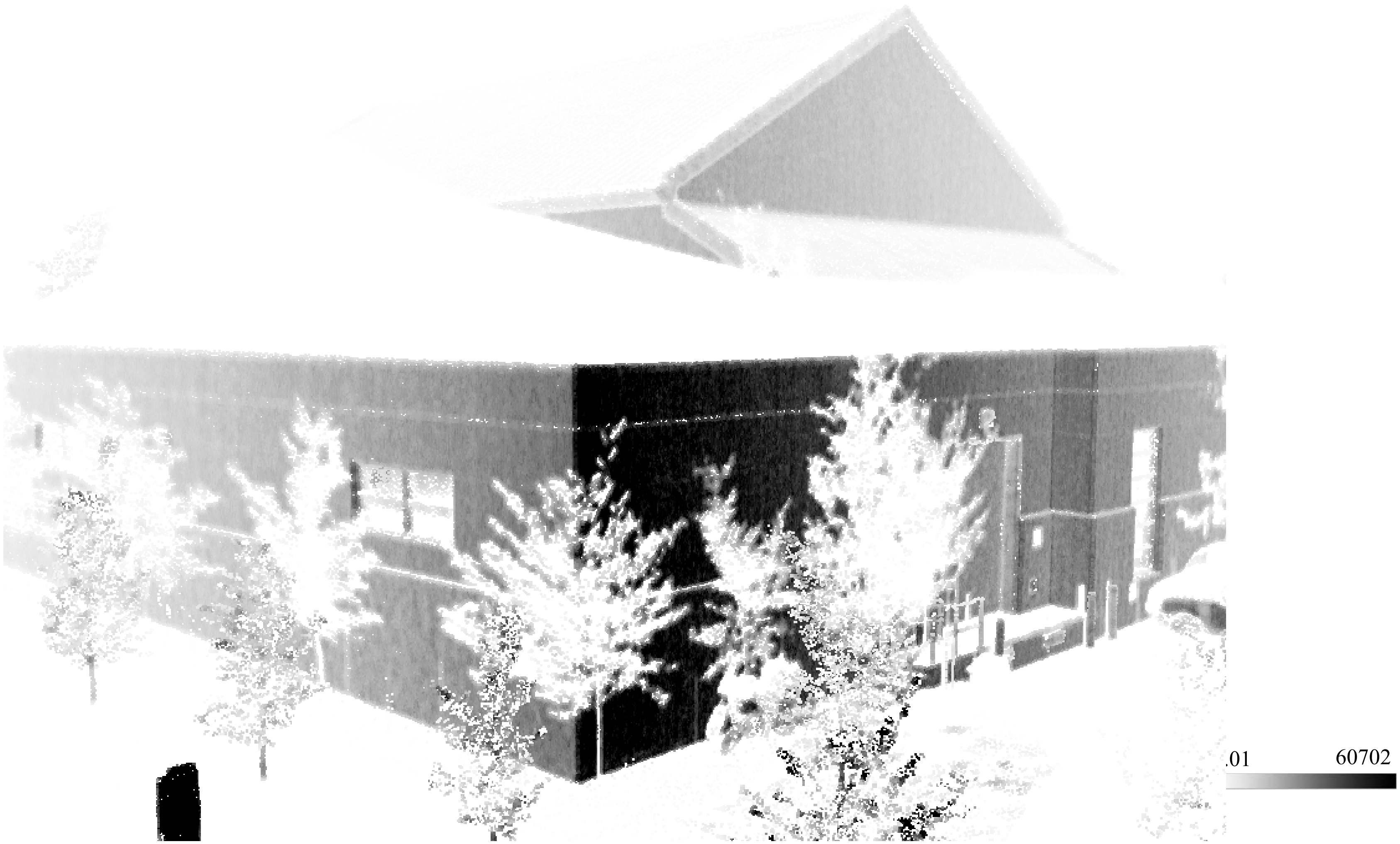
Experimental Results (Terrestrial Data)

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



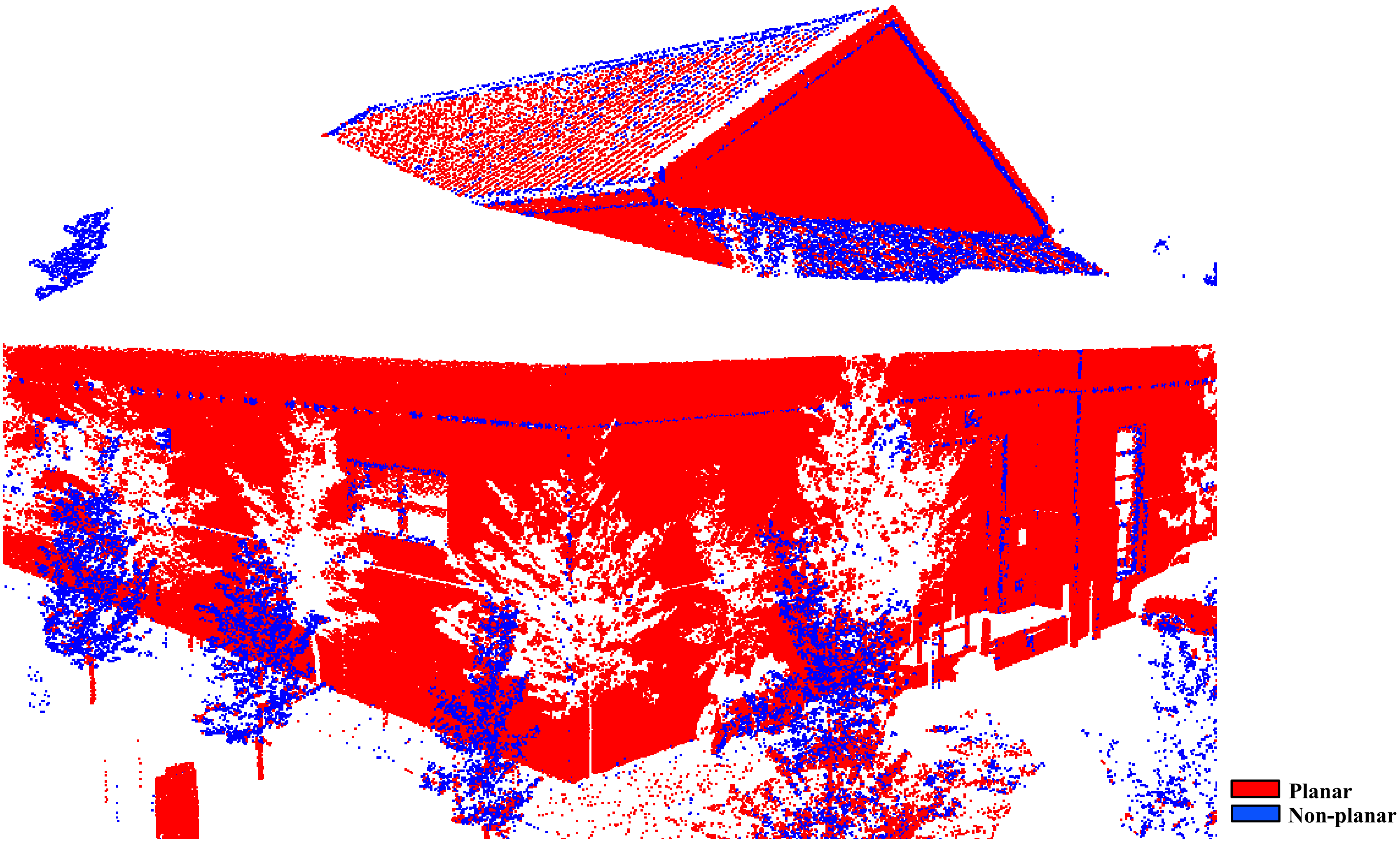
Experimental Results (Terrestrial Data)

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



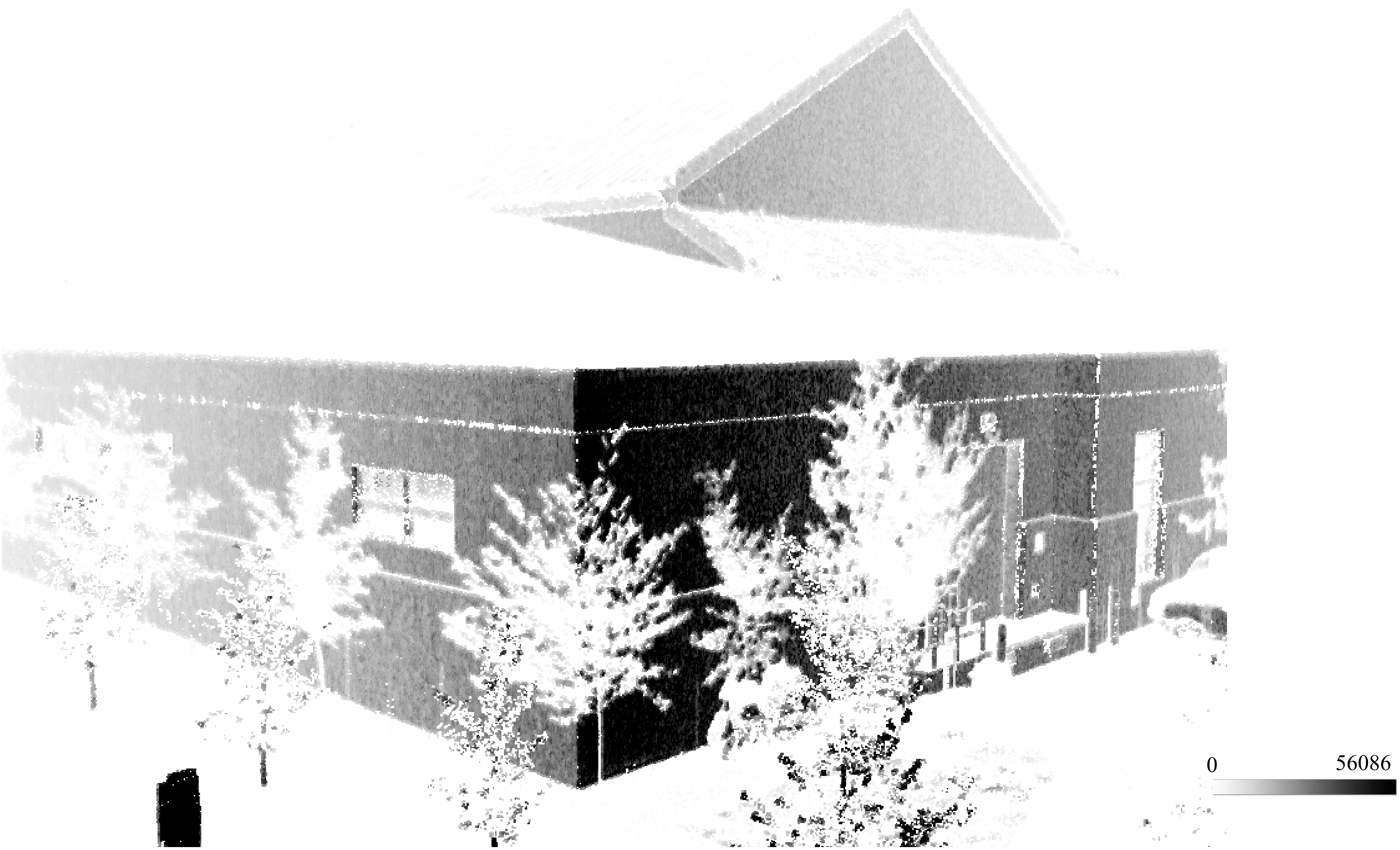
Experimental Results (Terrestrial Data)

- Adaptive cylinder:



Experimental Results (Terrestrial Data)

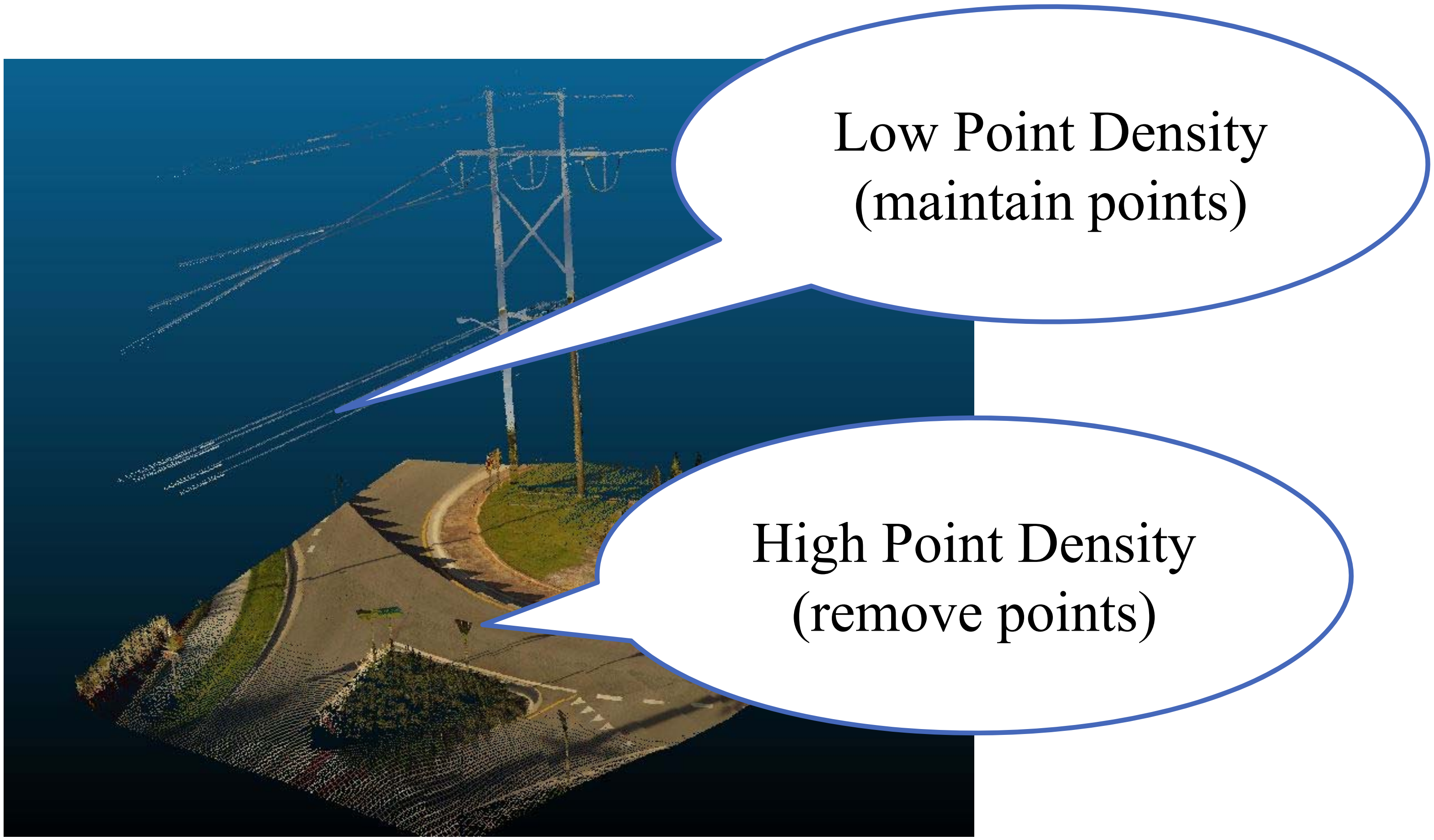
- Adaptive cylinder:



LiDAR Data Downsampling

LiDAR Data Downsampling: Introduction

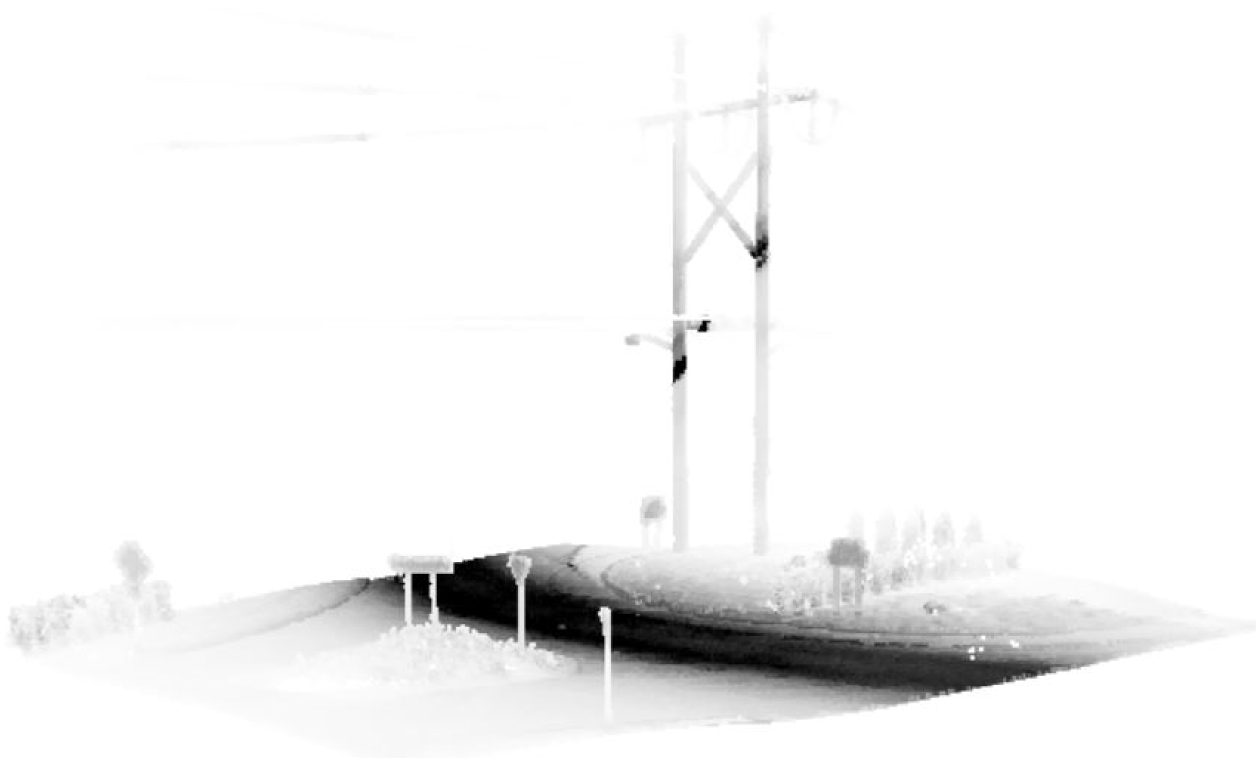
- LiDAR Data Down Sampling while maintaining the information content



LiDAR Data Downsampling: Introduction

- LiDAR Data Down Sampling while maintaining the information content

Original Data

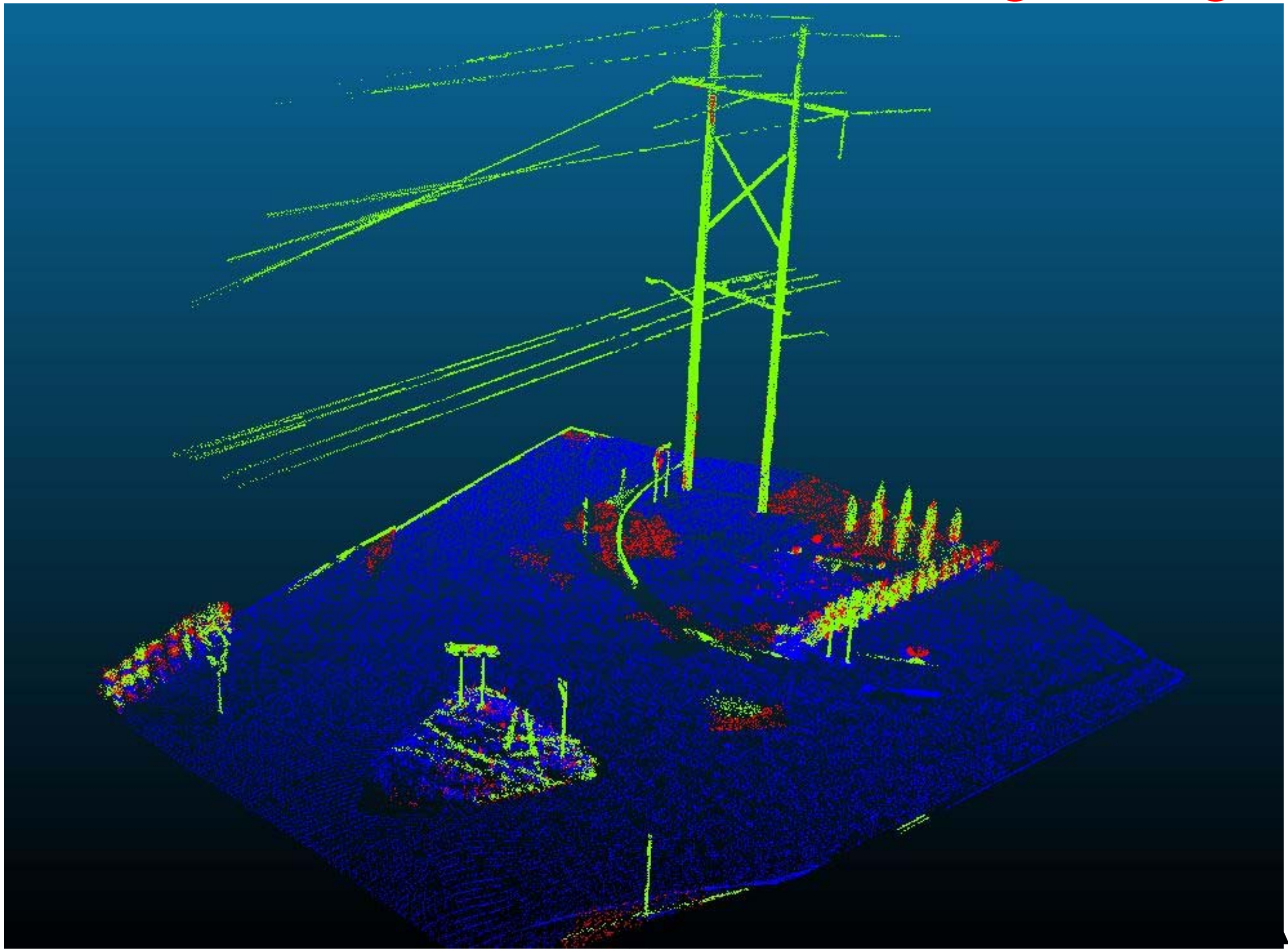


Darker points correspond to higher point density.

LiDAR Data Downsampling: Introduction

- LiDAR Data Down Sampling while maintaining the information content

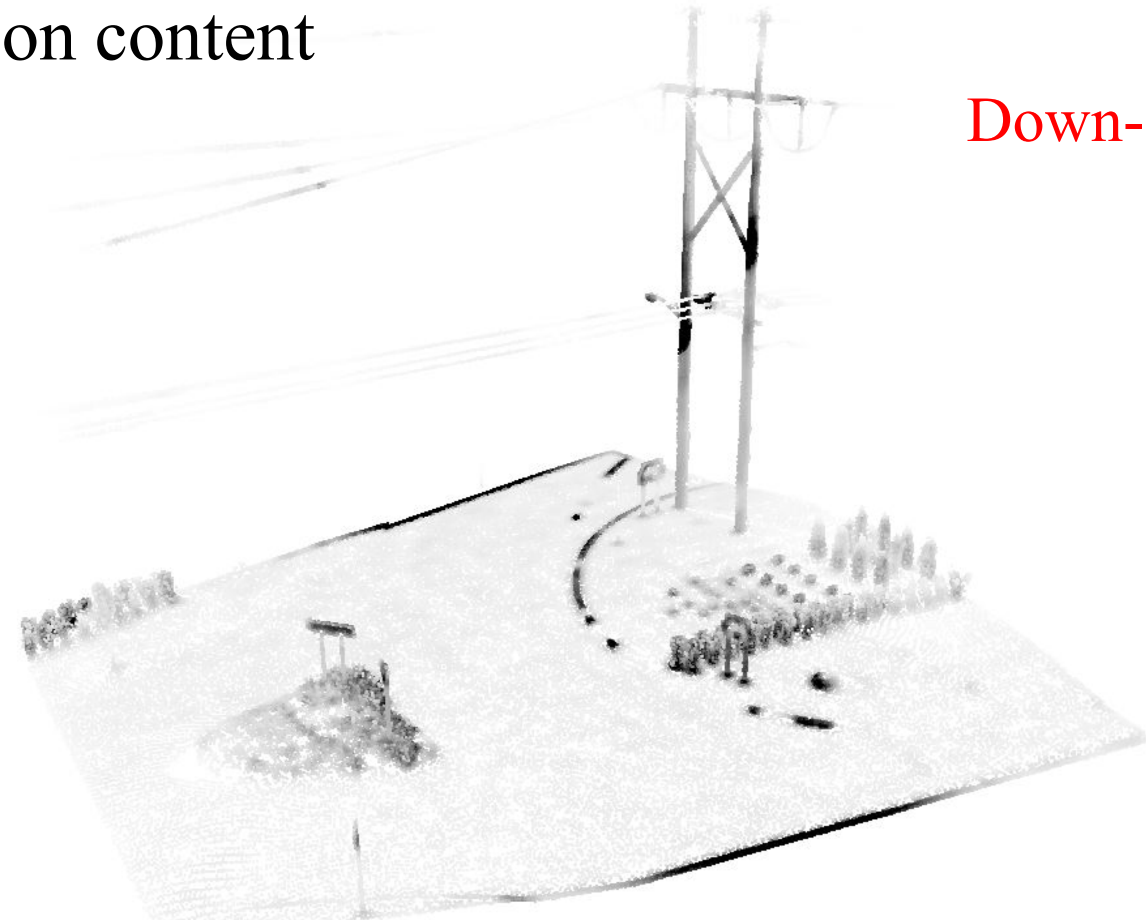
Original Segmented Data



LiDAR Data Downsampling: Introduction

- LiDAR Data Down Sampling while maintaining the information content

Down-sampled Data

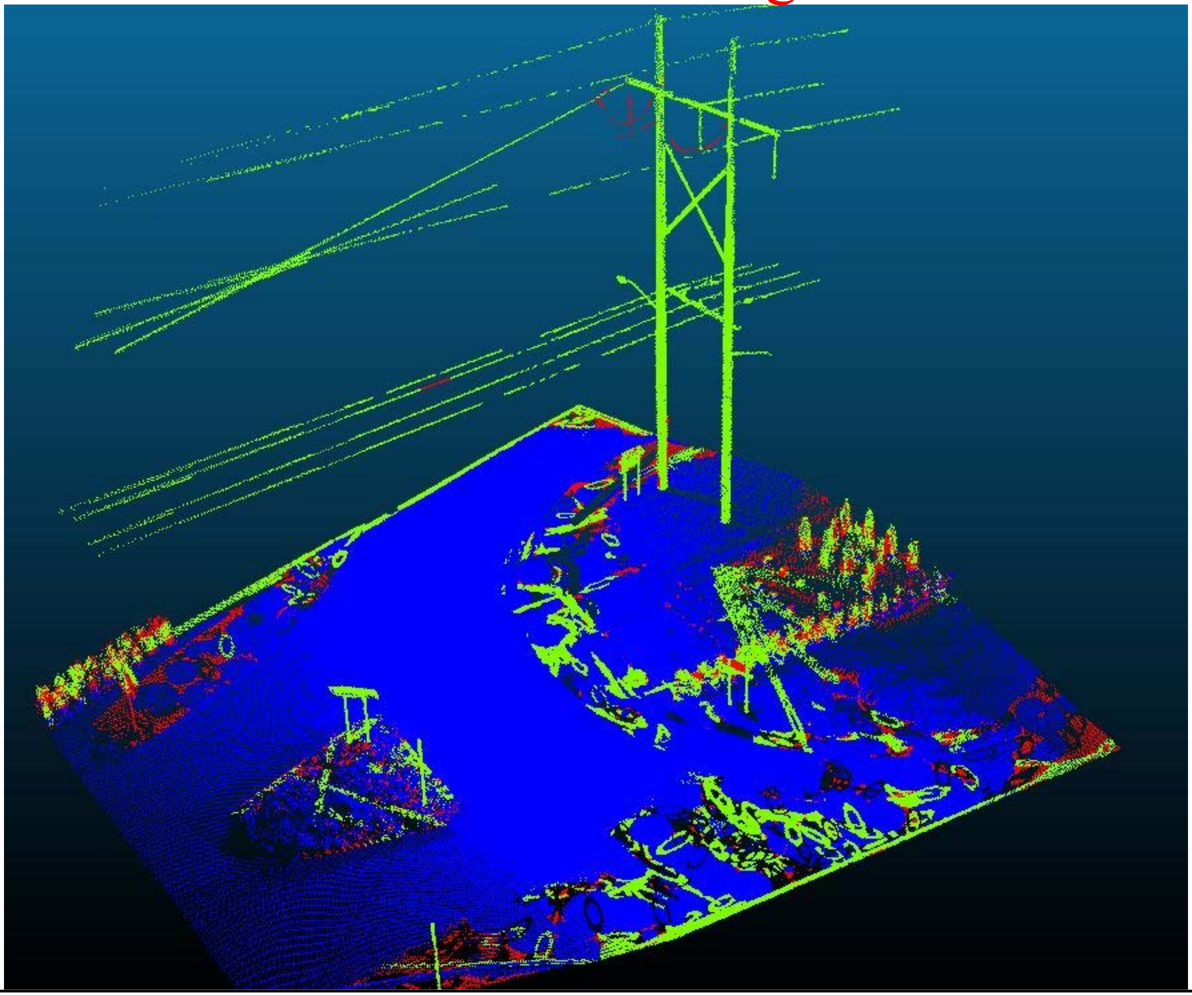


Darker points correspond to higher point density.

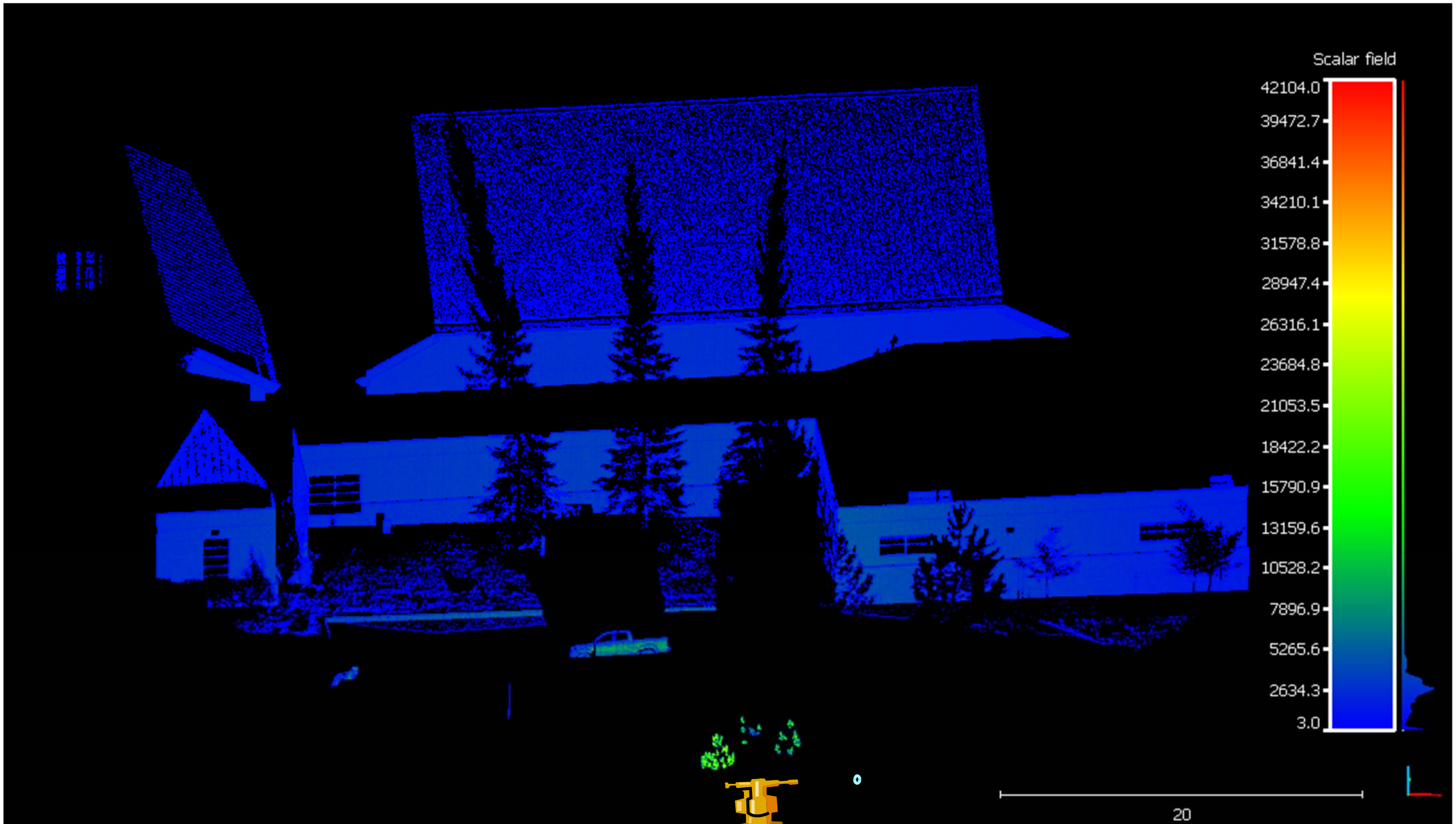
LiDAR Data Downsampling: Introduction

- LiDAR Data Down Sampling while maintaining the information content

Segmented Down-sampled Data



LiDAR Data Downsampling: Introduction



Density range up to 6000 pts/m^2

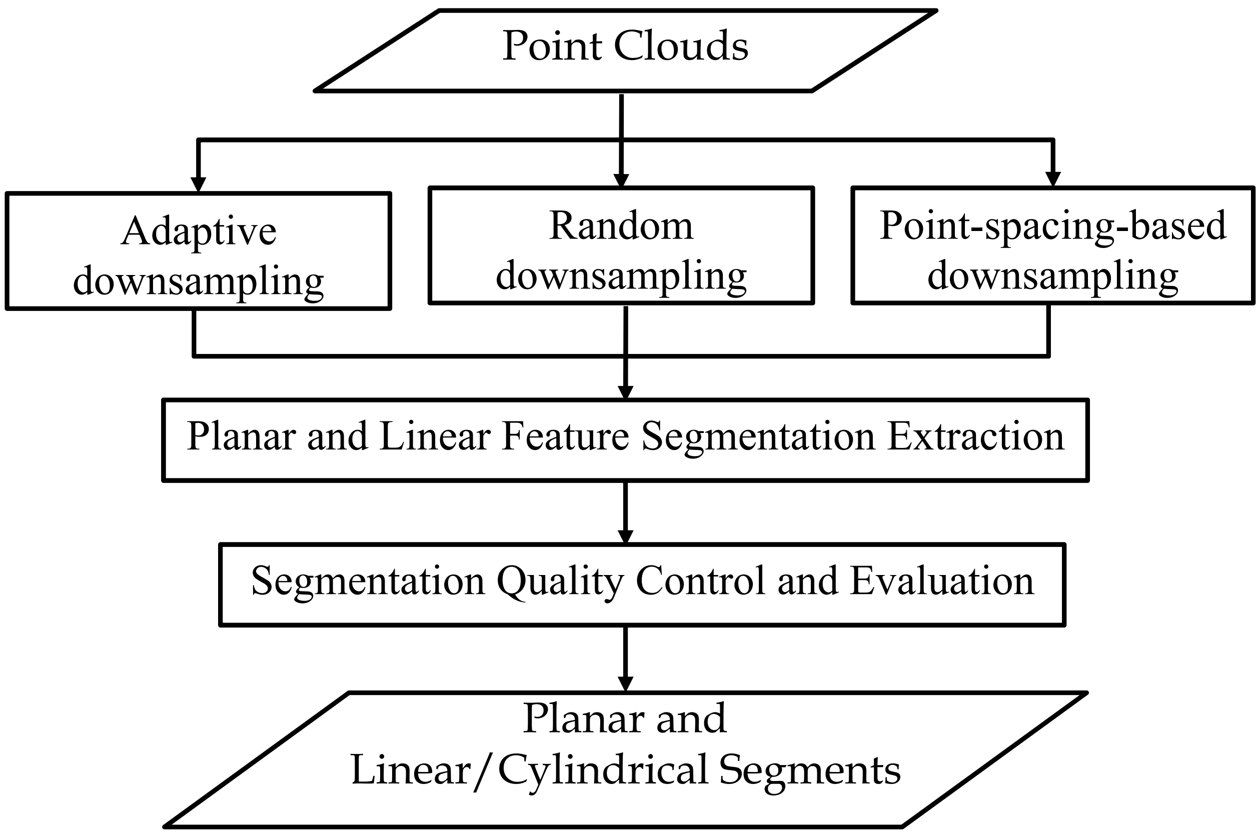
LiDAR Data Downsampling: Motivation

- A downsampling process can help in reducing the segmentation execution time.
- An inappropriate downsampling might compromise the segmentation results.
- Current methods do not consider the characteristics of the physical surface during the downsampling process:
  - Uniform downsampling
  - Distance-based downsampling

LiDAR Data Downsampling: Objectives

- Propose an adaptive downsampling procedure that only removes redundant points.
  - More points are removed in areas with high point density.
  - The majority of points will be maintained in areas with less point density.
  - The downsampling should consider the nature of the encompassing physical surface.
- Evaluation Criteria: Compare the segmentation results from original and thinned point clouds using different downsampling techniques.

Adaptive Downsampling: Methodology



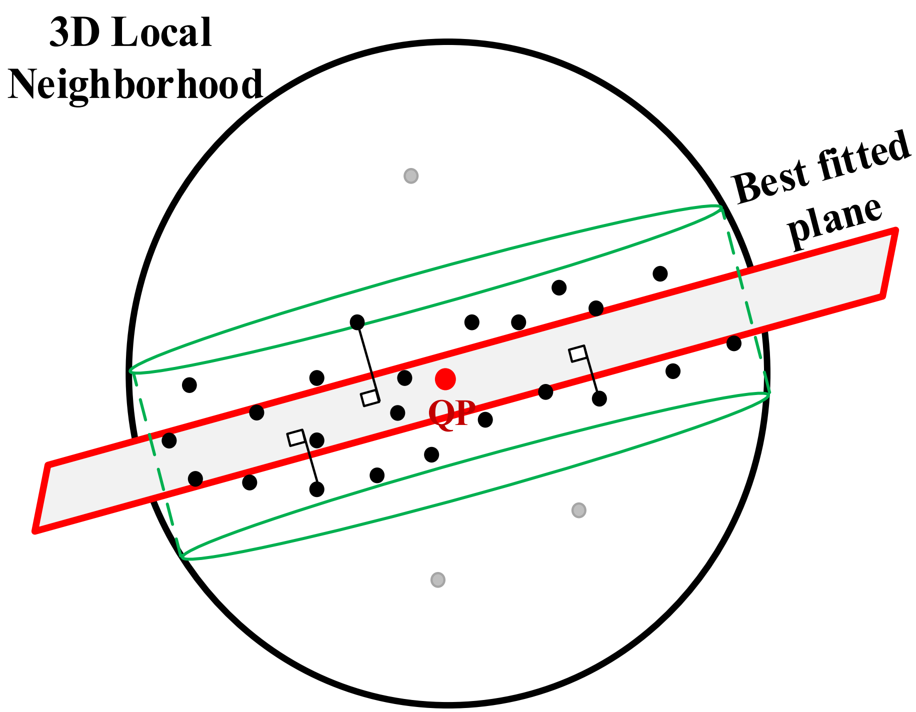
Adaptive Downsampling: Methodology

- Purpose: Remove points in high density areas and keep the points in low density areas.

- Procedure:
  - Calculate the point density
  - Adaptive downsampling

Adaptive Downsampling: Methodology

- Local Point Density (LPD) Estimation:



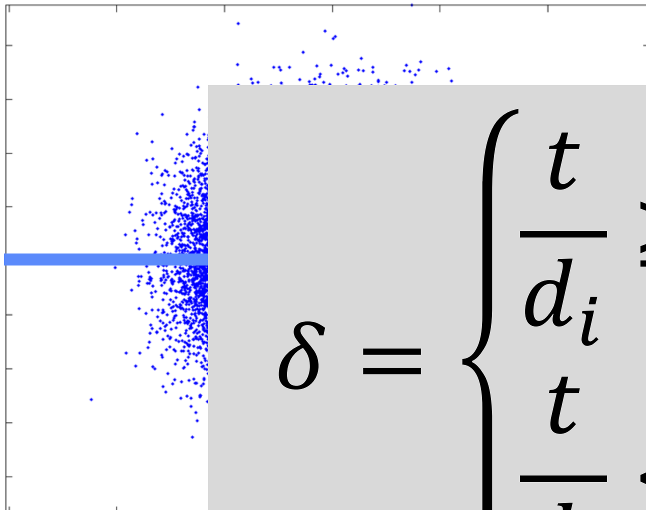
The points within the established 3D neighborhood are considered for local point density estimation if:

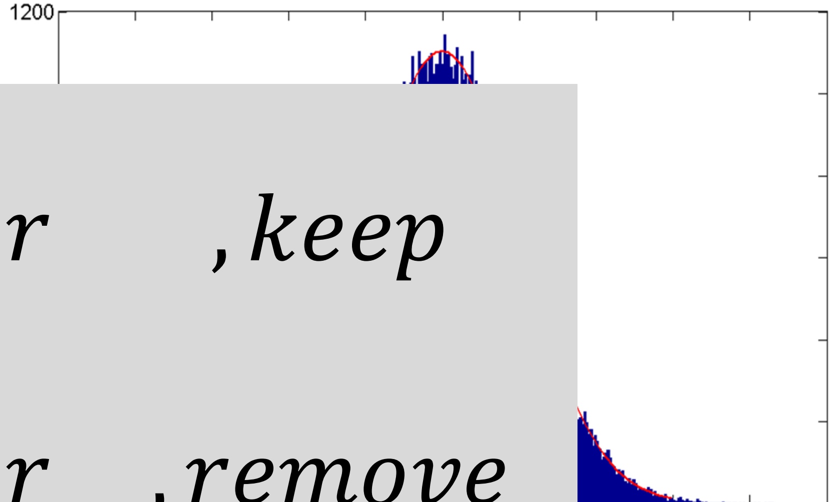
- They belong to the derived adaptive cylinder.

$$LPD\ (\text{pnts/m}^2) = \frac{k}{\pi r_n^2}$$

k	Number of points within the adaptive cylinder
r_n	The distance between the POI and its n^{th}-farthest neighbor

Adaptive Downsampling: Methodology





Sam

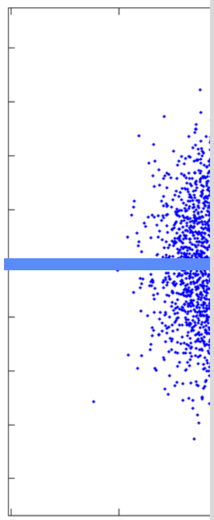
$$\delta = \begin{cases} \dfrac{t}{d_i} \geq r & ,keep \\ \dfrac{t}{d_i} < r & ,remove \end{cases}$$

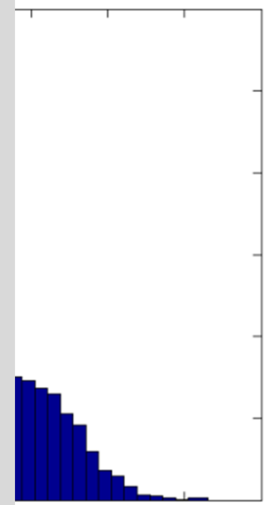
where,

t: *desired density*

d_i: *density of point i*

r: $\mathrm{U} \in [0 - 1]$

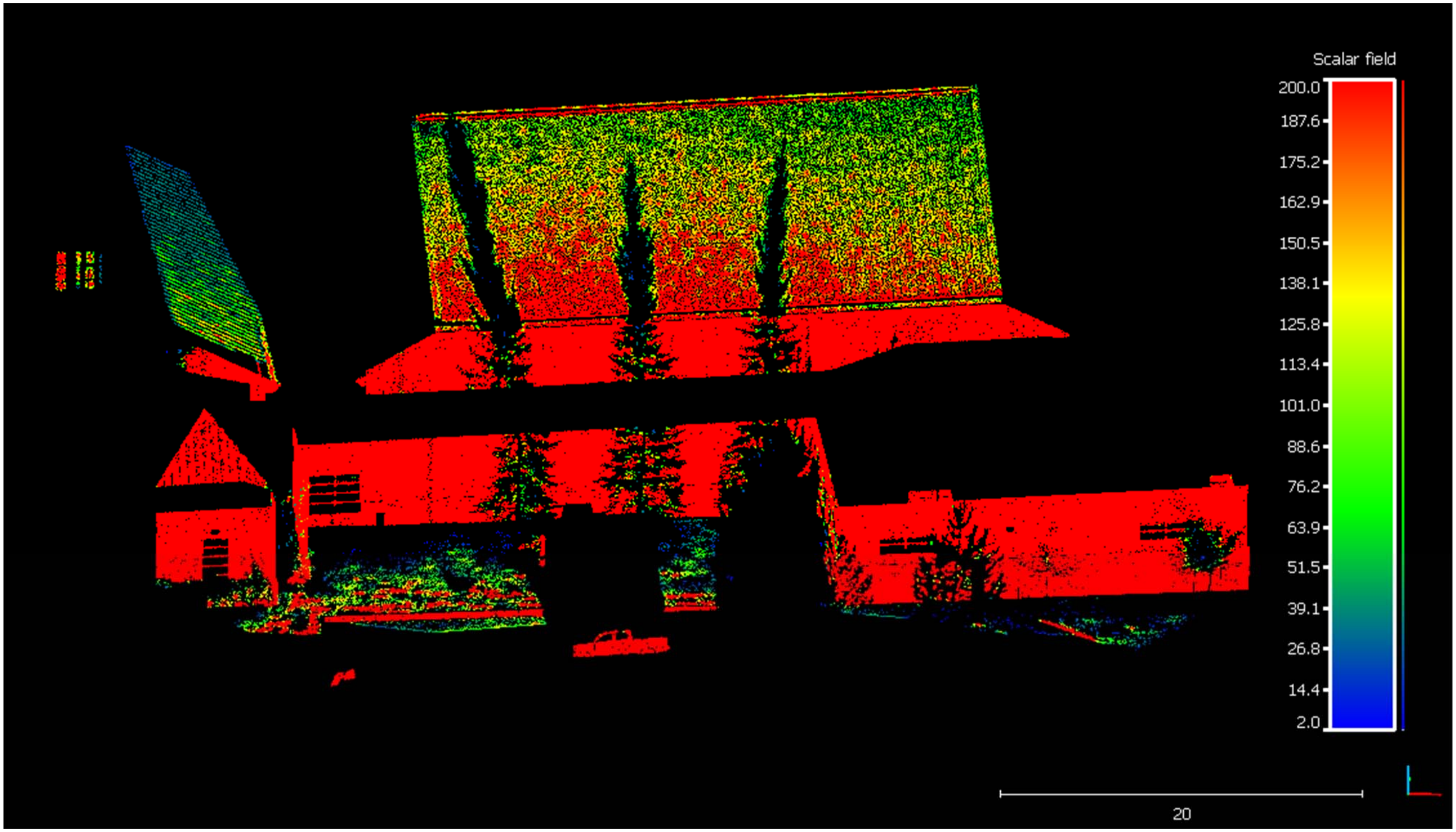




Downsampled point cloud

Histogram

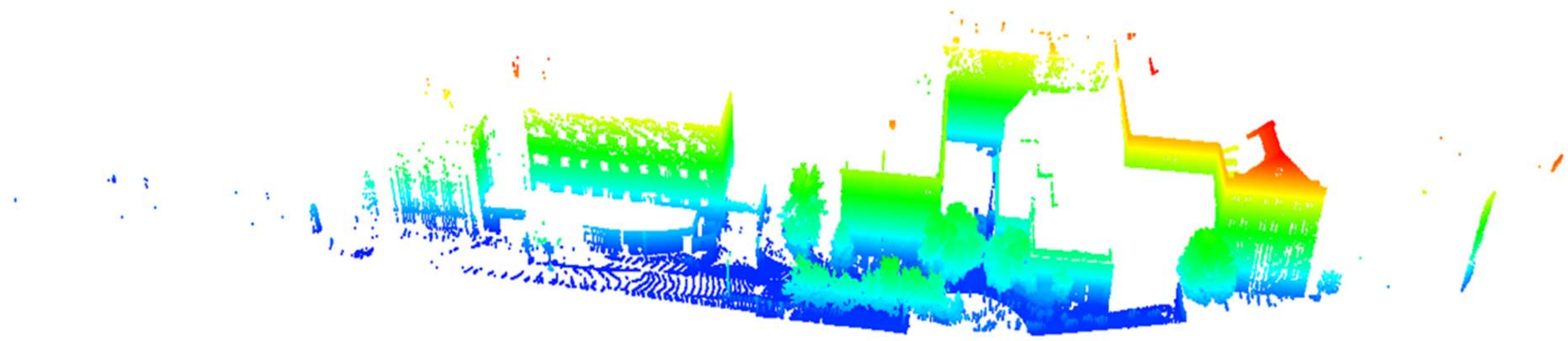
Adaptive Downsampling



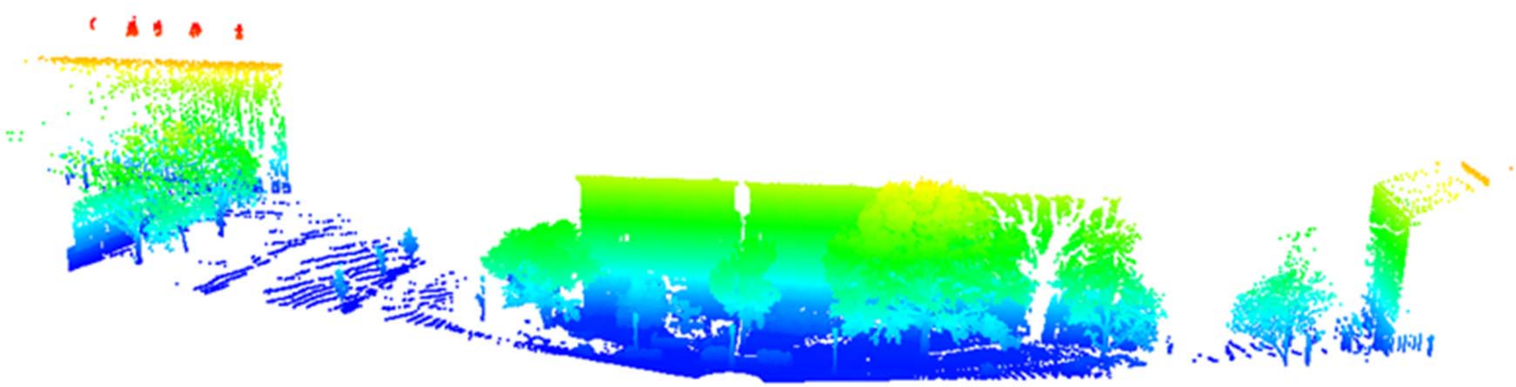
Density range up to 200 pts/m²

Experimental Results

- Dataset 1 --- Original dataset (STLS)

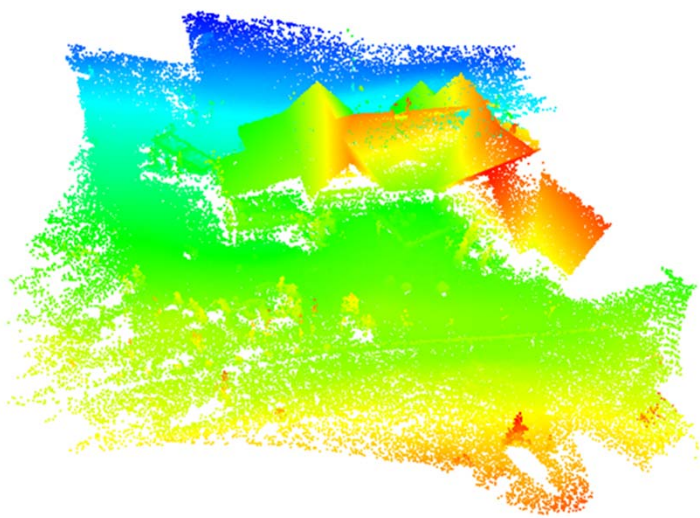


- Dataset 2 --- Original dataset (STLS)



Experimental Results

- Dataset 3 --- Original dataset (UAV)



Experimental Results

- The original and downsampled datasets are tested.

- Original Dataset Specifications

	Dataset 1	Dataset 2	Dataset 3
Number of points	2,765,436	785,243	230,434
Max. Point Density (pts/m^2)	562,239	24,071	1,264
Min. Point Density (pts/m^2)	0.002	0.002	0.092
Mean point density (pts/m^2)	6,808	1,996	109

Experimental Results

- We set different desired point density values for the adaptive downsampling.
- The inter-point spacing is set based on the desired point density
- Random downsampling is applied using "Cloudcompare" to have the same number of points as the adaptively downsampled dataset.

	Adaptive downsampling Desired point density (pts/m^2)	Point-spacing-based downsampling Min. spacing between points (m)
Dataset 1	220	0.0674
Dataset 2	200	0.0707
Dataset 3	50	0.1414

Experimental Results

- Statistics for the point-density values for the original and downsampled datasets
- Dataset 1

	Original	Adaptive downsampling	Random downsampling	Point-spacing-based downsampling
Dataset 1				
Number of Points	2,765,436	841,051	841,051	499,770
Max. Point Density (pts/m^2)	562,239.317	1,071.759	308,826.804	454.679
Min. Point Density (pts/m^2)	0.002	0.002	0.000	0.001
Mean point density (pts/m^2)	6,807.726	178.526	2,000.476	108.672

Experimental Results

- Statistics for the point-density values for the original and downsampled datasets
- Dataset 2

	Original	Adaptive downsampling	Random downsampling	Point-spacing-based downsampling
Dataset 2				
Number of Points	785,243	343,237	343,237	223,957
Max. Point Density (pts/m^2)	24,071.217	946.743	19,103.060	386.271
Min. Point Density (pts/m^2)	0.002	0.002	0.002	0.002
Mean point density (pts/m^2)	1,995.906	151.371	947.618	90.557

Experimental Results

- Statistics for the point-density values for the original and downsampled datasets
- Dataset 3

	Original	Adaptive downsampling	Random downsampling	Point-spacing-based downsampling
Dataset 3				
Number of Points	230,434	137,219	137,219	74,785
Max. Point Density (pts/m^2)	1,264.293	188.815	849.833	53.950
Min. Point Density (pts/m^2)	0.092	0.092	0.090	0.090
Mean point density (pts/m^2)	108.988	43.310	66.195	22.126

Experimental Results

- Segmentation execution time for the different datasets

	Time **(hh:mm:ss)**			
Dataset	Original Dataset	Adaptive downsampling dataset	Random downsampling dataset	Point-spacing-based downsampling dataset
1	01:10:46	00:11:30	00:17:51	00:05:17
2	00:33:17	00:05:43	00:06:00	00:02:51
3	00:03:31	00:01:33	00:01:41	00:00:50

Experimental Results

- Dataset 1 – Original Data

  - Planar Segments before Quality Control

  - Planar Segments after Quality Control

STLS Dataset

Experimental Results

- Dataset 1 – Adaptive downsampling

- Planar Segments before Quality Control

- Planar Segments after Quality Control

STLS Dataset

Experimental Results

- Dataset 1 – Random downsampling

  - Planar Segments before Quality Control

  - Planar Segments after Quality Control

STLS Dataset

Experimental Results

- Dataset 1 – Point-spacing-based downsampling

  - Planar Segments before Quality Control

Incomplete Incorrect

  - Planar Segments after Quality Control

STLS Dataset

Experimental Results

- Dataset 2 – Original Data

- Planar Segments before Quality Control

- Planar Segments after Quality Control

STLS Dataset

Experimental Results

- Dataset 2 – Adaptive downsampling

  - Planar Segments before Quality Control

  - Planar Segments after Quality Control

STLS Dataset

Experimental Results

- Dataset 2 – Random downsampling

  - Planar Segments before Quality Control

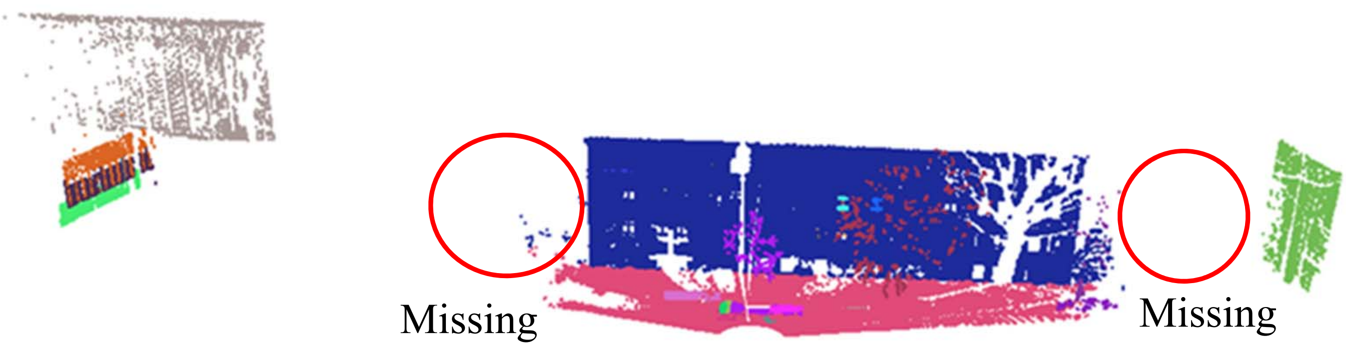
  - Planar Segments after Quality Control

STLS Dataset

Experimental Results

- Dataset 2 – Point-spacing-based downsampling

  - Planar Segments before Quality Control

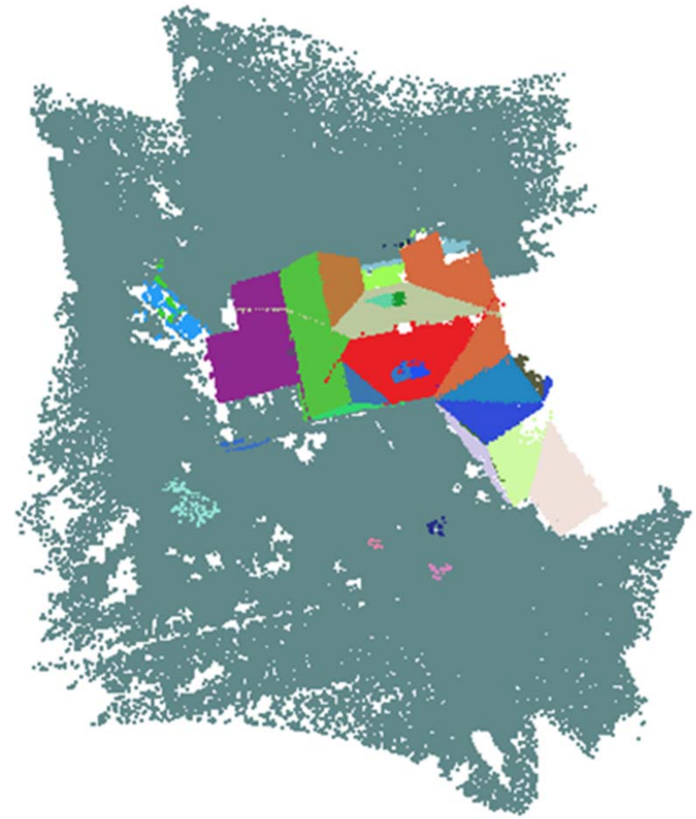


  - Planar Segments after Quality Control

STLS Dataset

Experimental Results

- Dataset 3 – Original Data

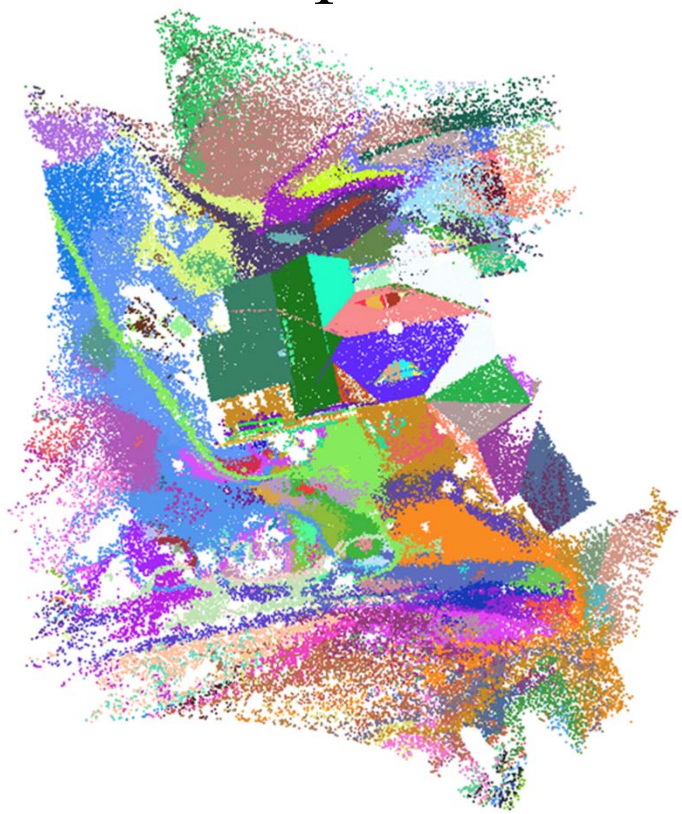


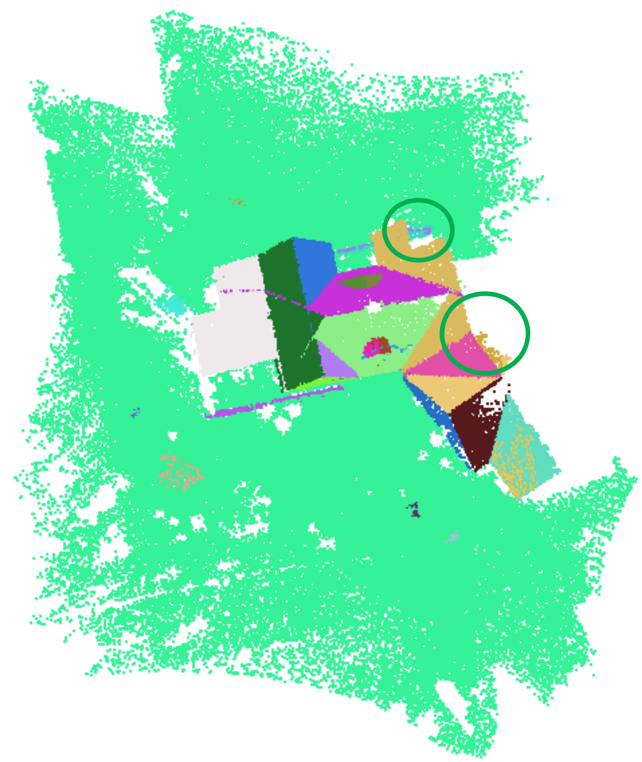
- Planar Segments before Quality Control
- Planar Segments after Quality Control

UAV Dataset

Experimental Results

- Dataset 3 – Adaptive downsampling



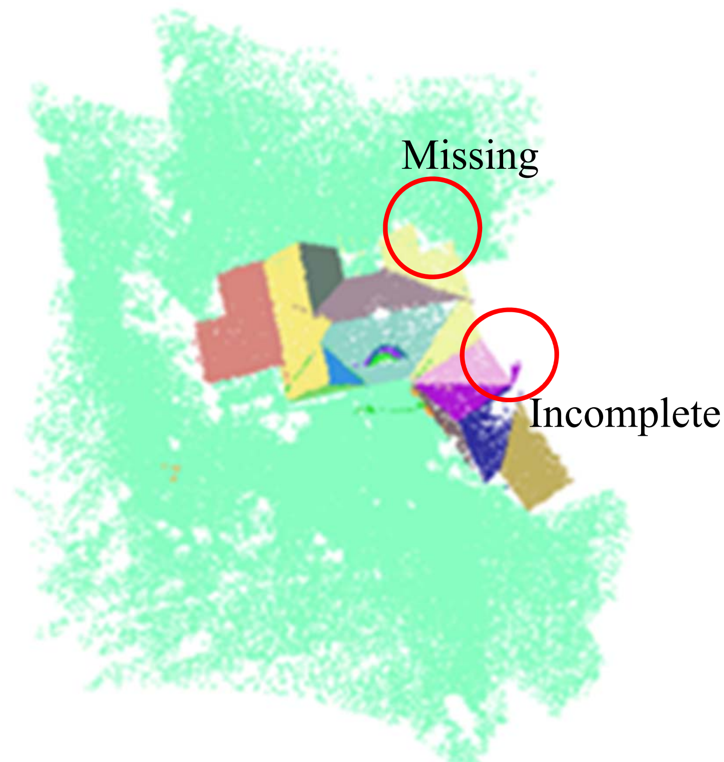


- Planar Segments before Quality Control
- Planar Segments after Quality Control

UAV Dataset

Experimental Results

- Dataset 3 – Random downsampling

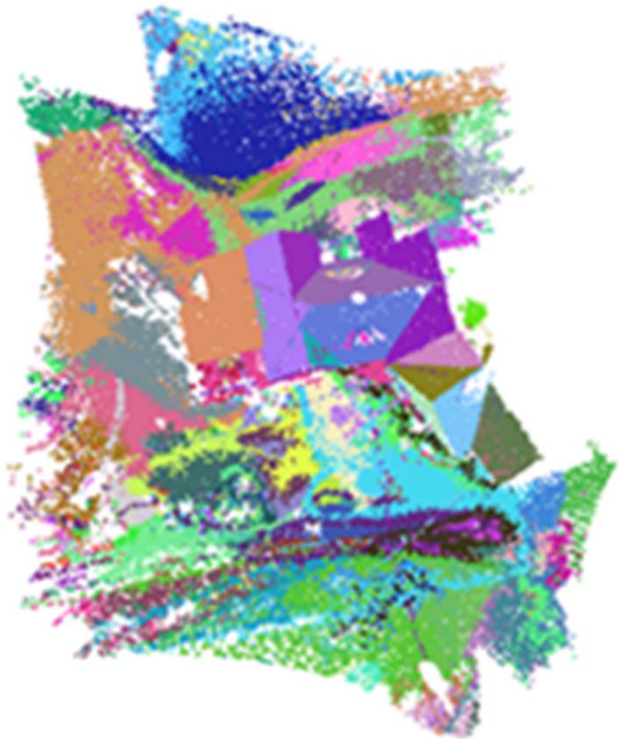


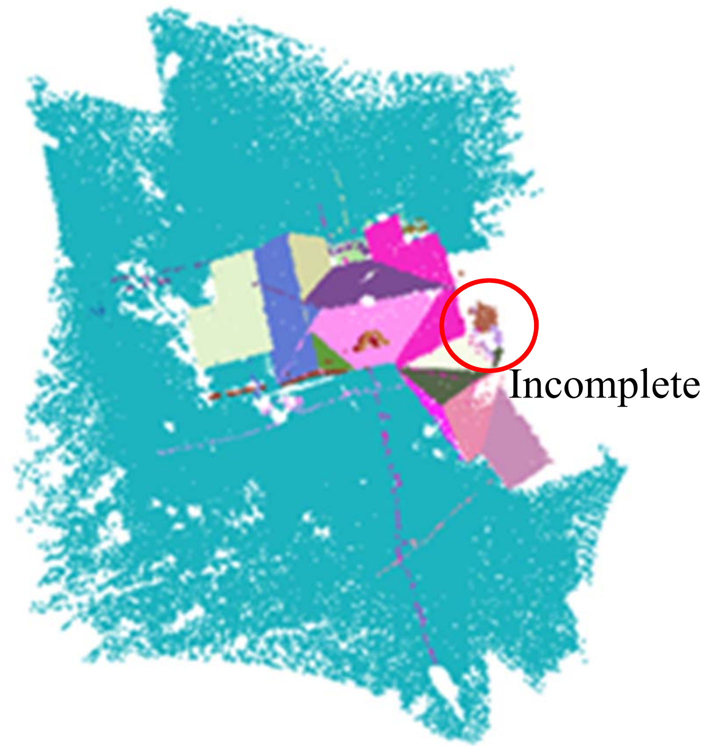
- Planar Segments before Quality Control
- Planar Segments after Quality Control

UAV Dataset

Experimental Results

- Dataset 3 – Point-spacing-based downsampling





- Planar Segments before Quality Control
- Planar Segments after Quality Control

UAV Dataset

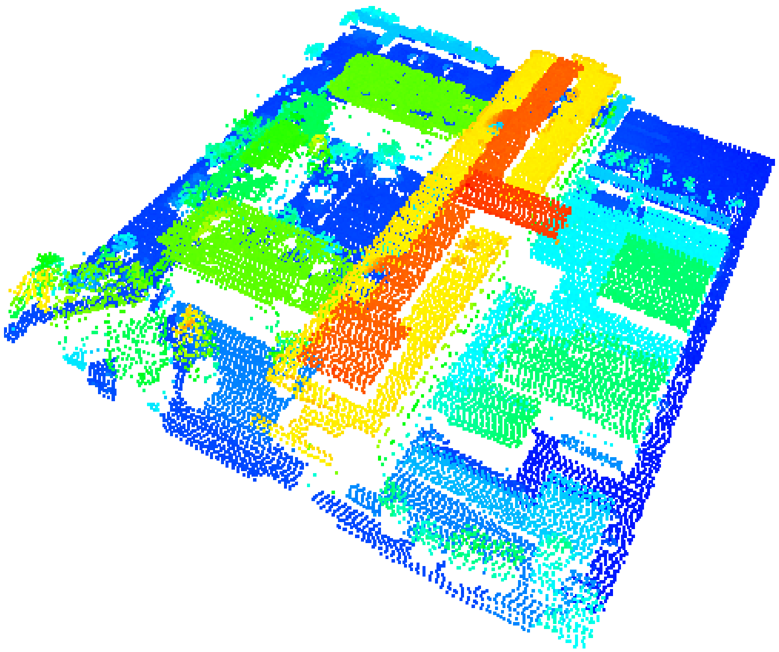
Concluding Remarks

- We introduced an adaptive downsampling strategy while comparing its performance through point density and segmentation results for three downsampled datasets.
- Compared with other methods, the adaptive downsampling provides the closest mean point density to the desired one.
- After the segmentation, the adaptive downsampling strategy maintained the major details in the different datasets.
- We are working on more intelligent adaptive downsampling as well as quantitative approaches for evaluating the performance of the different downsampling strategies.

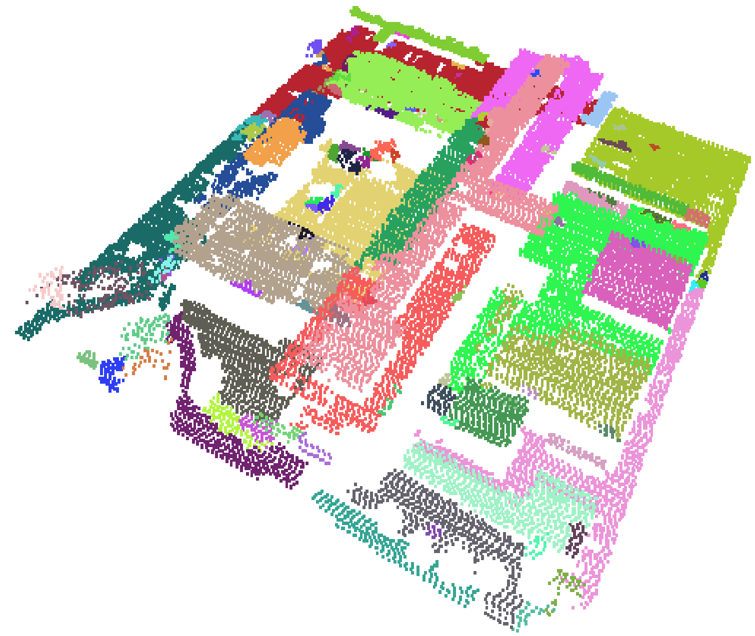
LiDAR Data Segmentation

LiDAR Data Segmentation

- **Segmentation Process:** Abstraction of the LiDAR points into distinct regions whose constituents share similar attributes.
  - Segmentation is usually considered as the prerequisite step for feature extraction and data interpretation.



Original point cloud



Segmented point cloud

LiDAR Data Segmentation: Previous Work

I. **Spatial-domain techniques** segment the point cloud based on the proximity of points and similarity of locally estimated attributes.
   - Dependency of the majority of these approaches on the selection of seed points
   - Sensitivity to noisy data
   - Non-optimal segmentation around edges where two surfaces meet

II. **Parameter-domain techniques** aggregate points with similar attributes into clusters in an attribute space.
   - Lack of computational efficiency when dealing with multidimensional attributes for a massive amount of points
   - Not considering the connectivity of the points in the object domain

Drawbacks:

- **Both techniques do not consider variations in the local point density within the segmentation process.**
- **There is no established procedure for quality control of the segmentation results.**

LiDAR Data Segmentation: Objectives

- Introduce new approaches for adaptive LiDAR data segmentation while considering **local point density variations**
- The developed approaches should be capable of dealing with heterogeneous laser scanning data.
- Quality control of the LiDAR data segmentation results
- Comparative analysis of spatial-domain and parameter-domain LiDAR data segmentation approaches

Spatial-Domain Segmentation

Heterogeneous Segmentation

Import LiDAR data

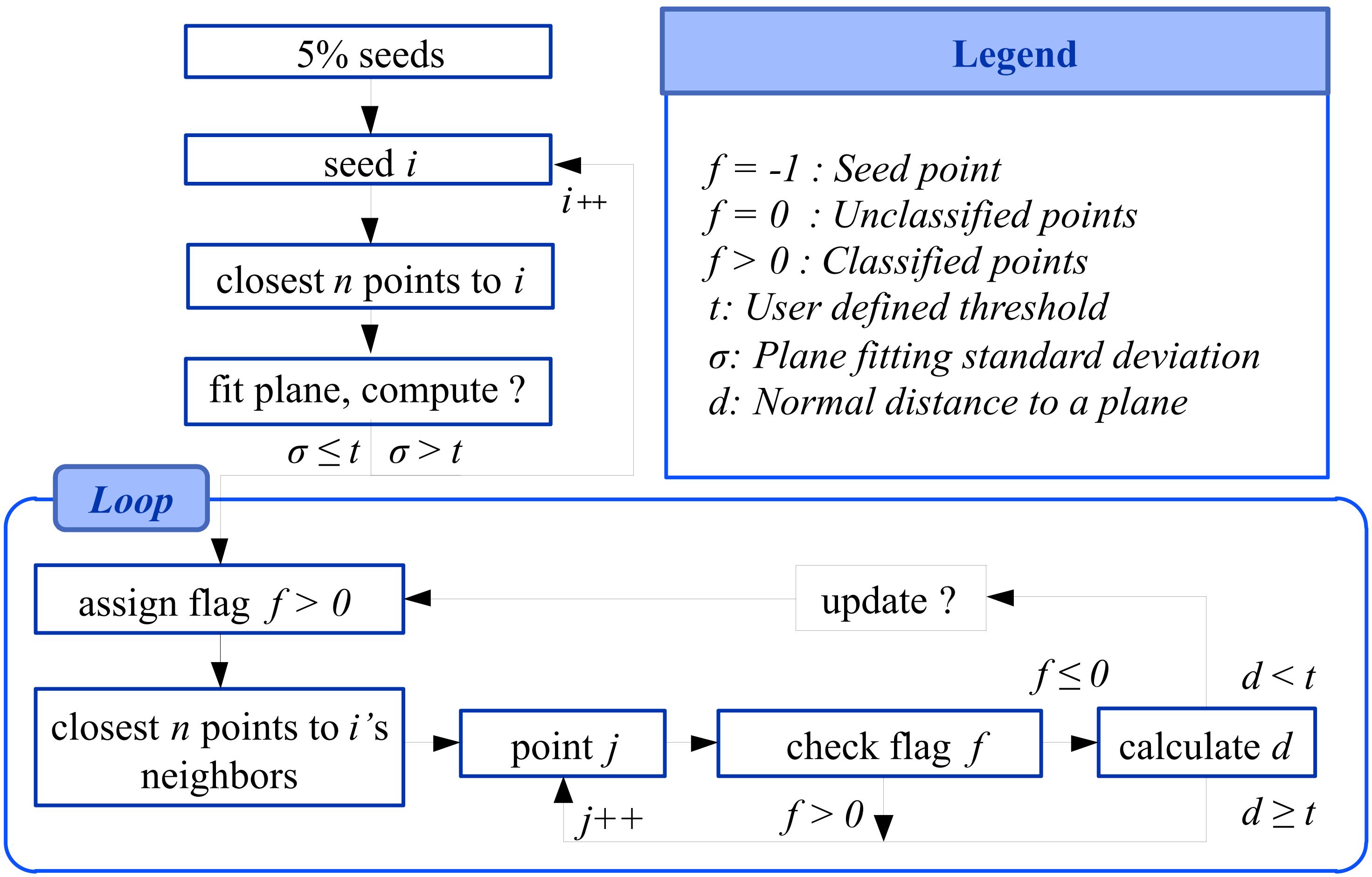
Single Scan Segmentation
(Estimate point density, surface roughness, and local surface normal)

Iterative Closest Projected Point (ICPP)

Heterogeneous Segmentation

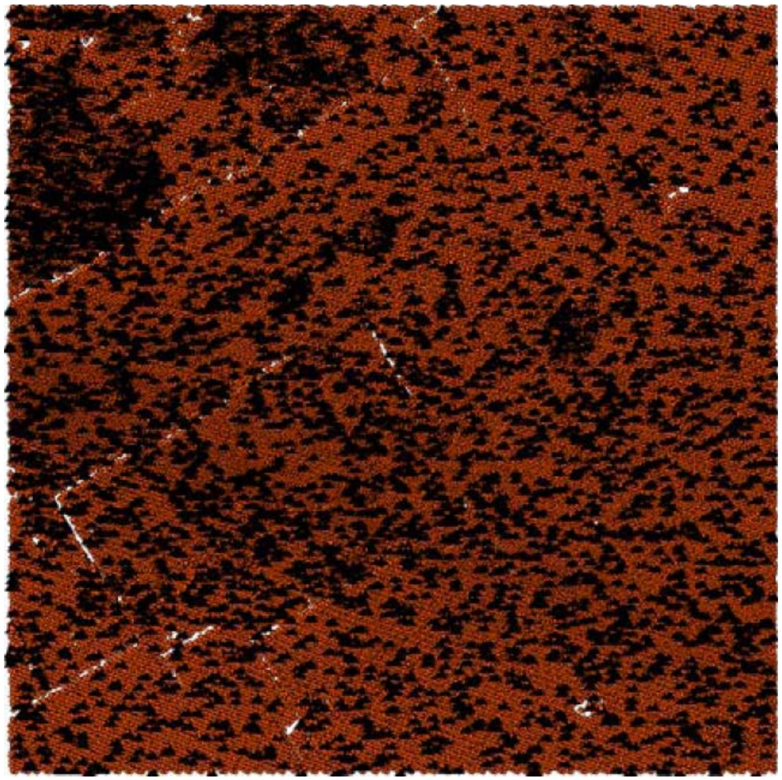
Spatial-Domain Segmentation

Single Scan Segmentation



Spatial-Domain Segmentation

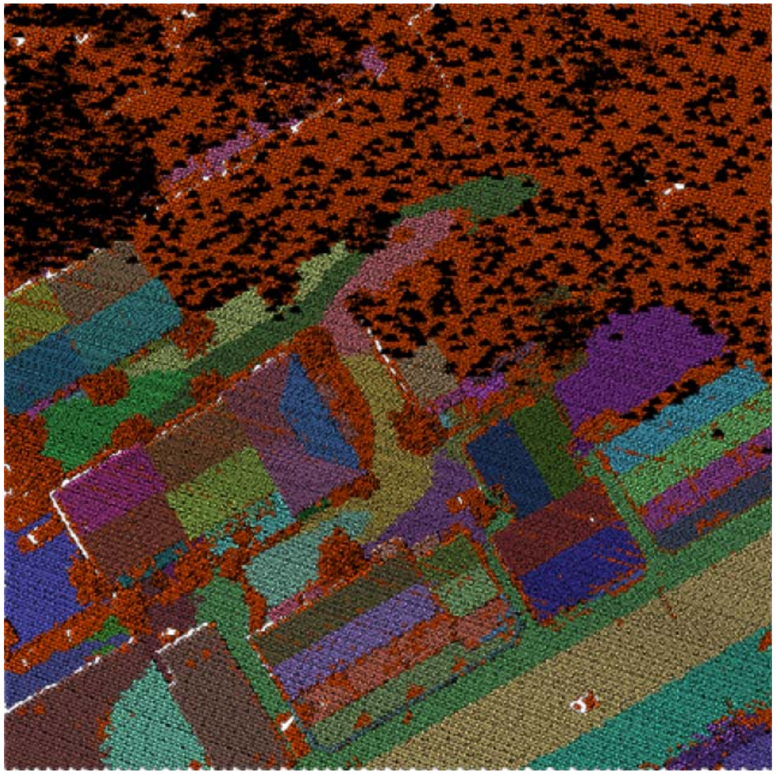
Single Scan Segmentation



A subset of collected airborne LiDAR points, where 5% of the points are randomly selected as seeds (dark points) for the region growing purposes

Spatial-Domain Segmentation

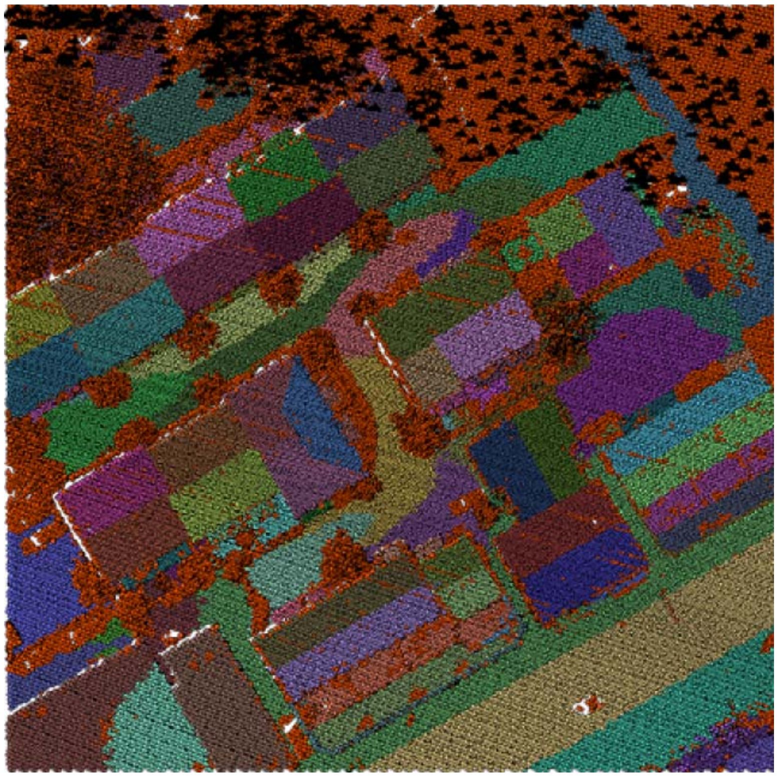
Single Scan Segmentation



The progress of the segmentation after processing 65% of the data points

Spatial-Domain Segmentation

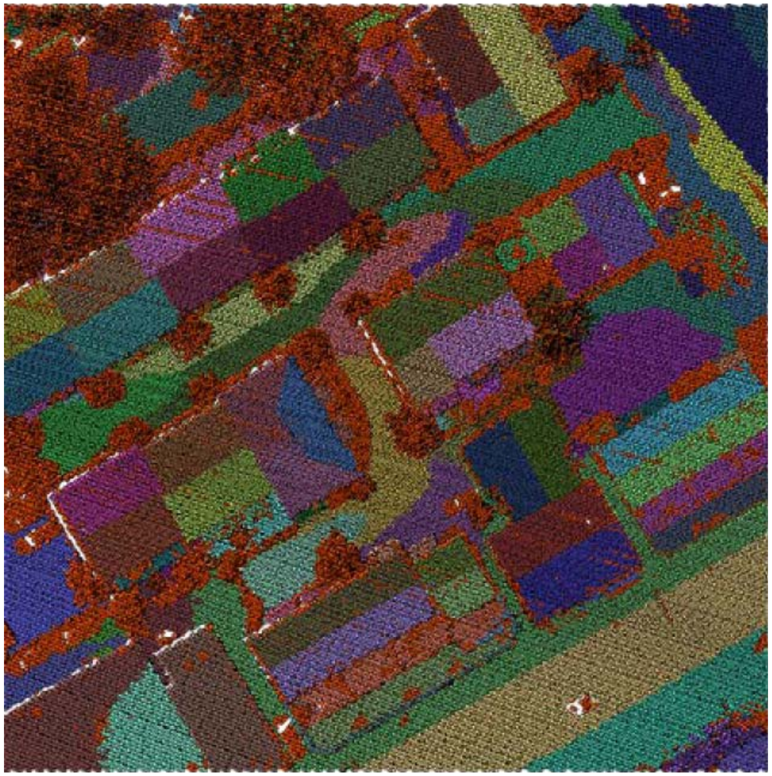
Single Scan Segmentation



The progress of the segmentation after processing 85% of the data points

Spatial-Domain Segmentation

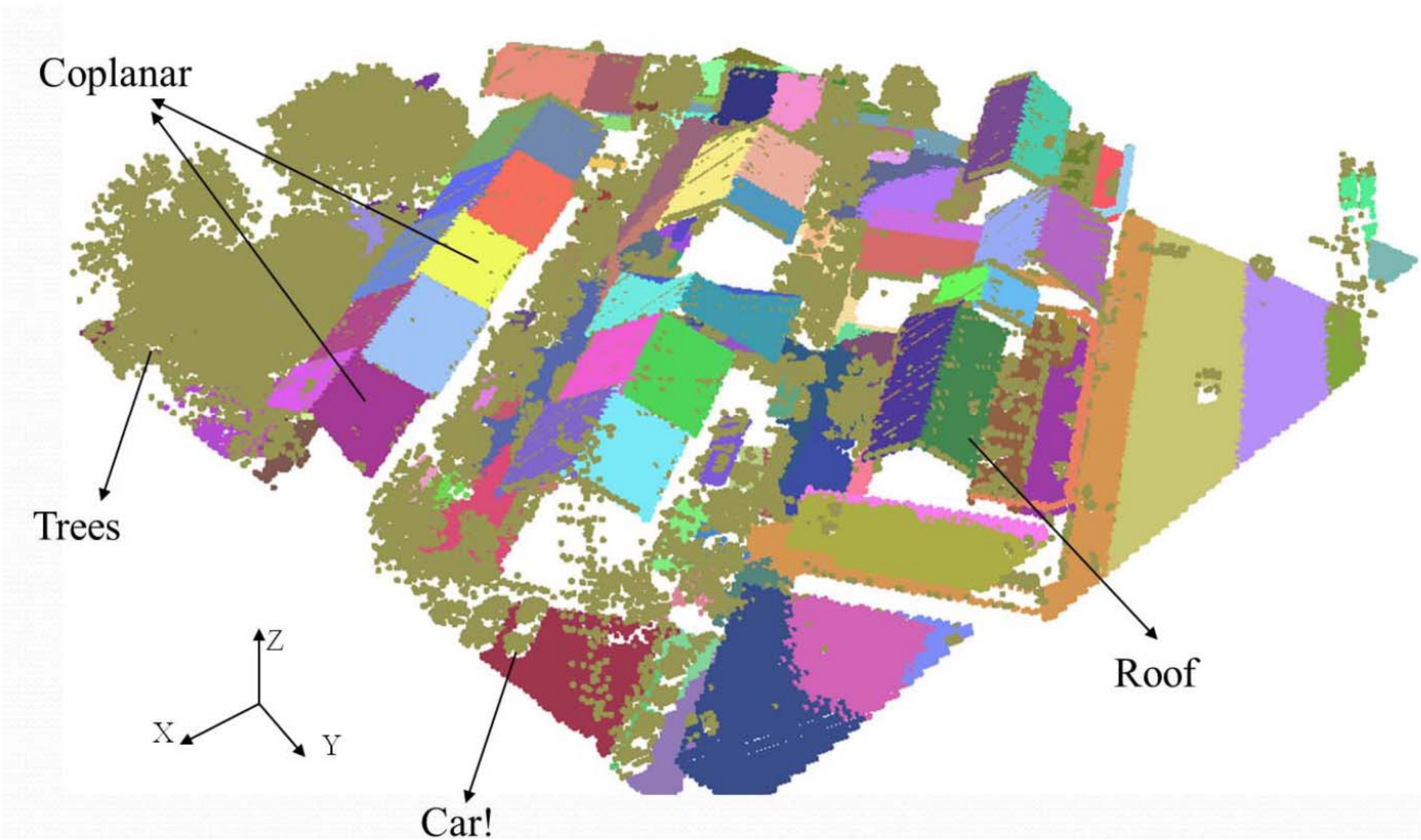
Single Scan Segmentation



The progress of the segmentation after processing 100% of the data points (non-segmented points are shown in dark orange)

Spatial-Domain Segmentation

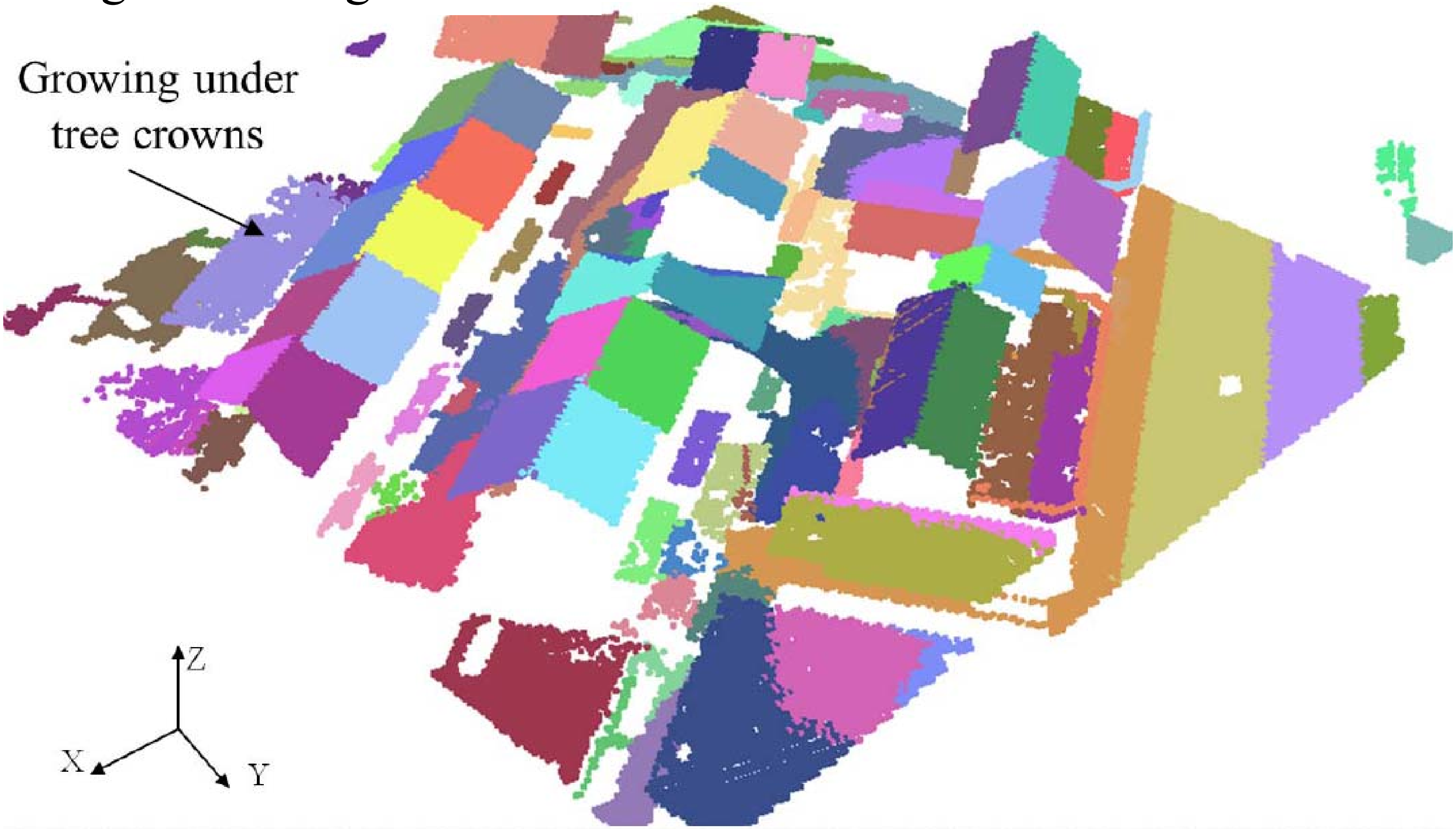
Single Scan Segmentation



Segmentation results (including non-segmented points)

Spatial-Domain Segmentation

Single Scan Segmentation



Segmentation results (excluding non-segmented points)

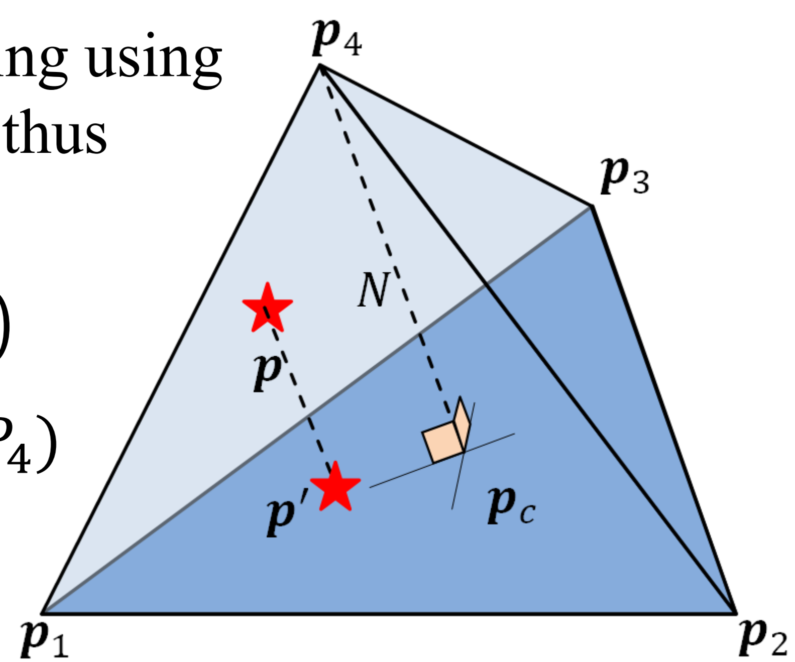
Spatial-Domain Segmentation

- Multi-Scan Registration: Iterative Closest Projected Point (ICPP)
- A match is established between a point in S_1 and a triangle (P_1, P_2, P_3) in S_2

- The pair (P, P′) is used for matching using the conventional ICP techniques, thus named the ICPP

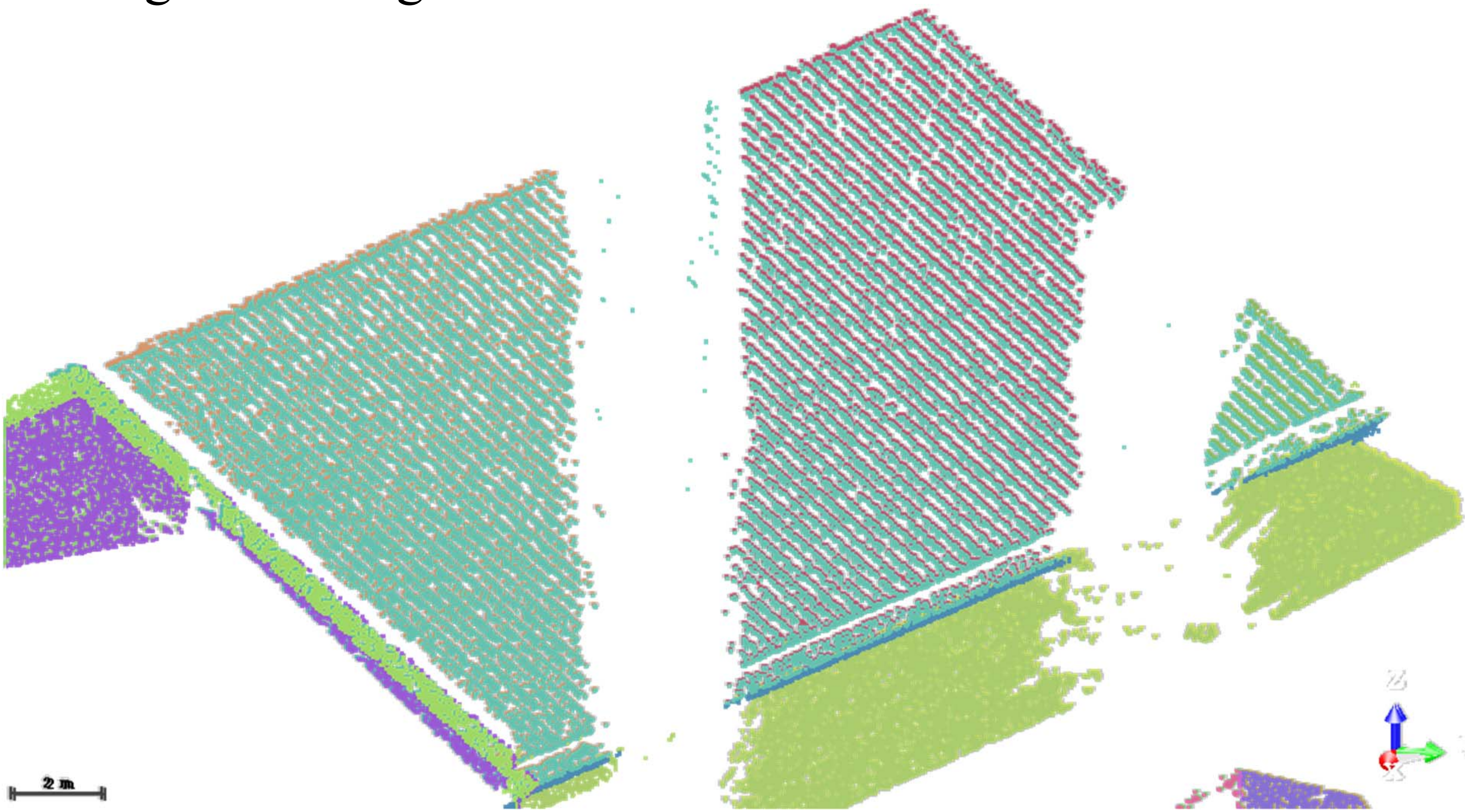
$$0 = \boldsymbol{T}_2 + \boldsymbol{R}_2\, \boldsymbol{p}' - \left(\boldsymbol{T}_1 + \boldsymbol{R}_1\, \boldsymbol{p}\right)$$

*Condition: $P \in Convex(P_1, P_2, P_3, P_4)$



Spatial-Domain Segmentation

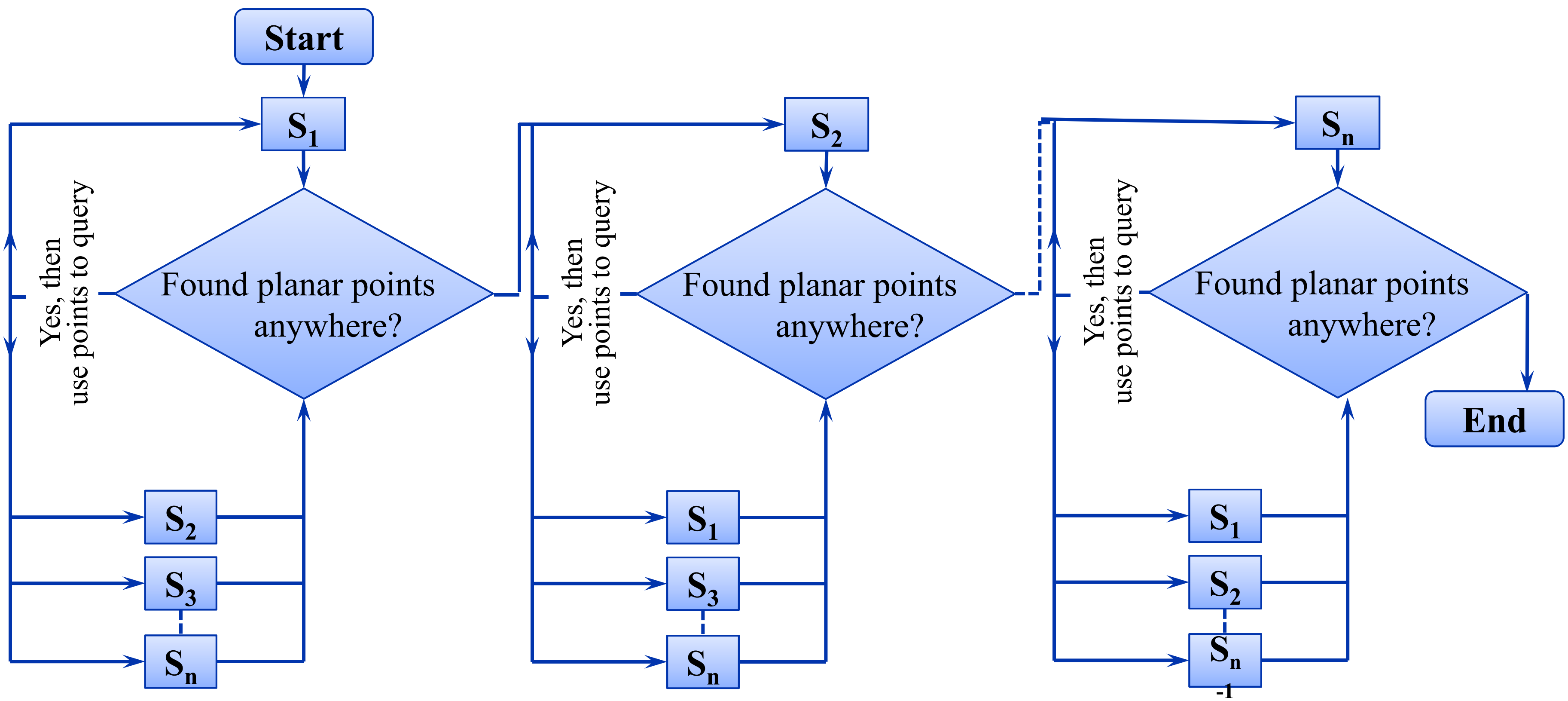
Heterogeneous Segmentation



Proper segmentation despite the presence of occlusion

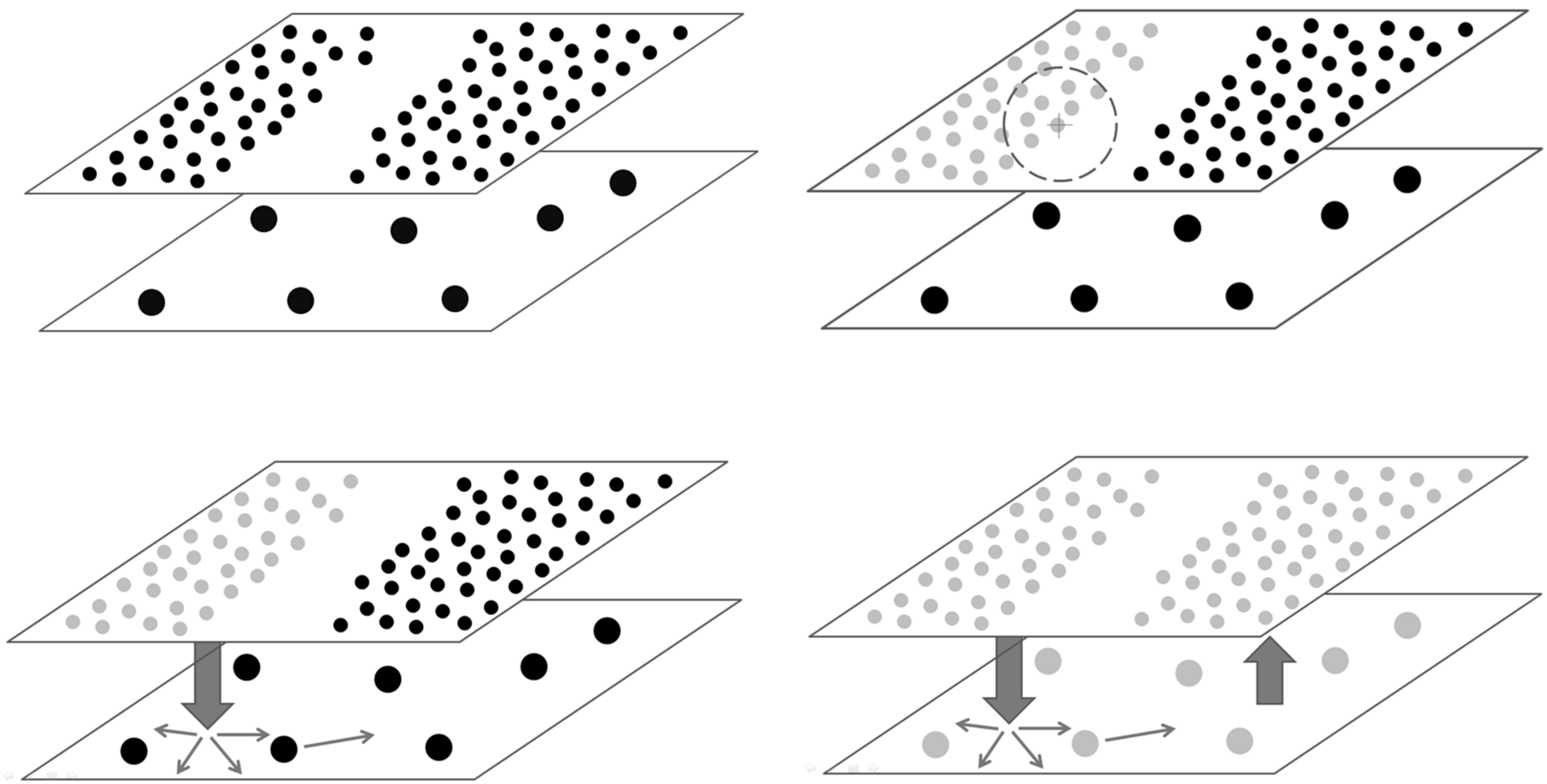
Spatial-Domain Segmentation

Heterogeneous Segmentation



Spatial-Domain Segmentation

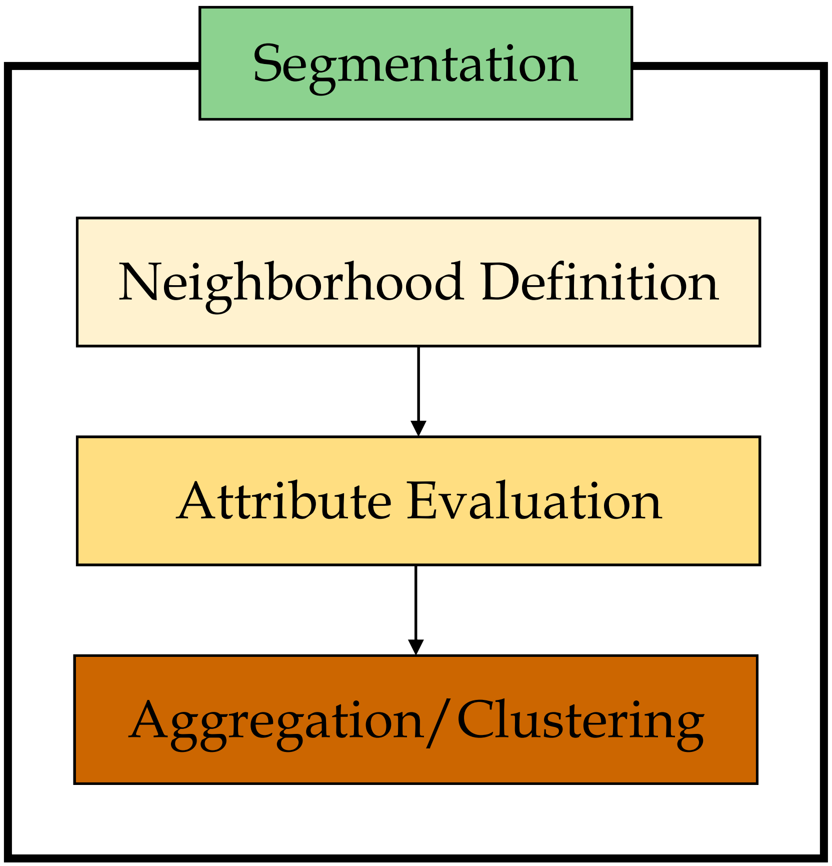
Heterogeneous Segmentation



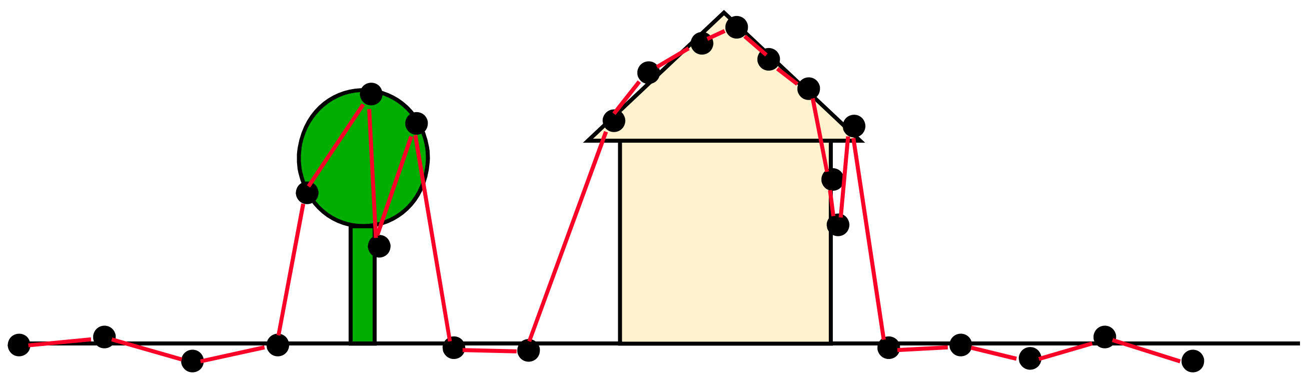
Parameter Domain Segmentation

Planar Segmentation

Conceptual Basis

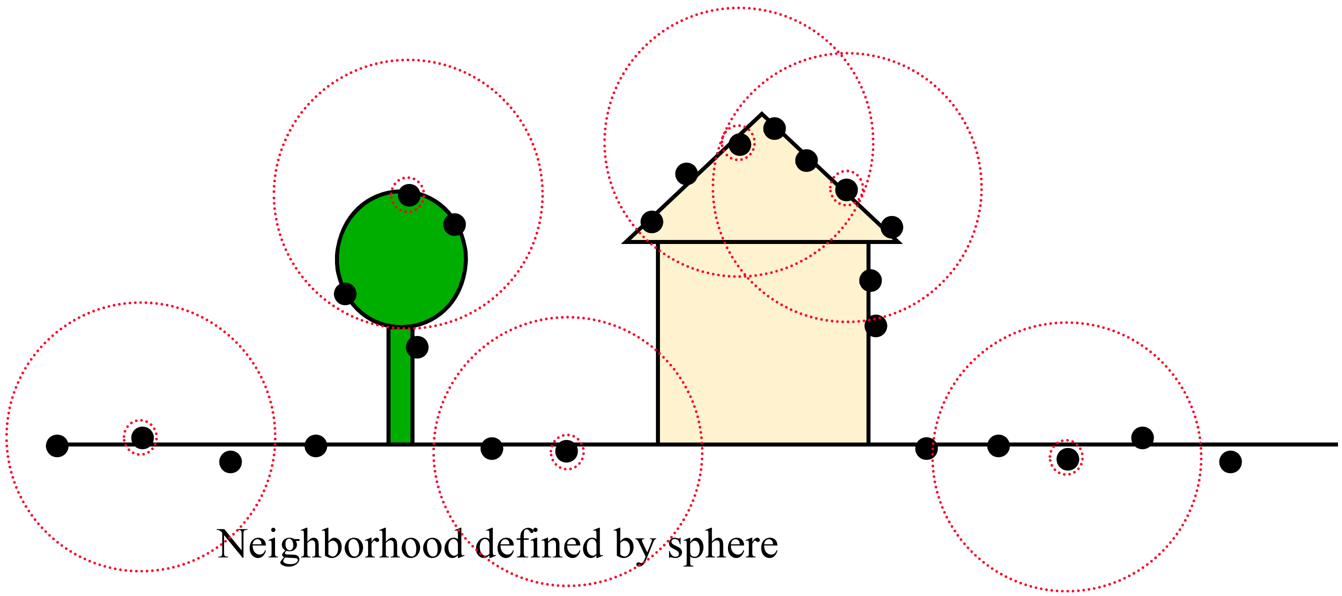


Neighborhood Definition



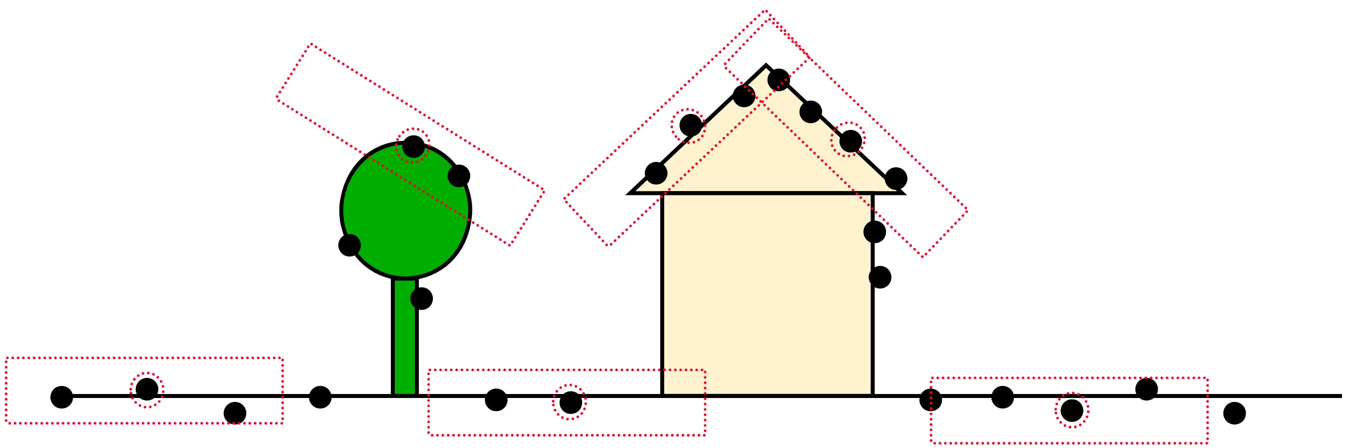
Neighborhood defined by triangulations

Neighborhood Definition



Neighborhood defined by sphere

Neighborhood Definition



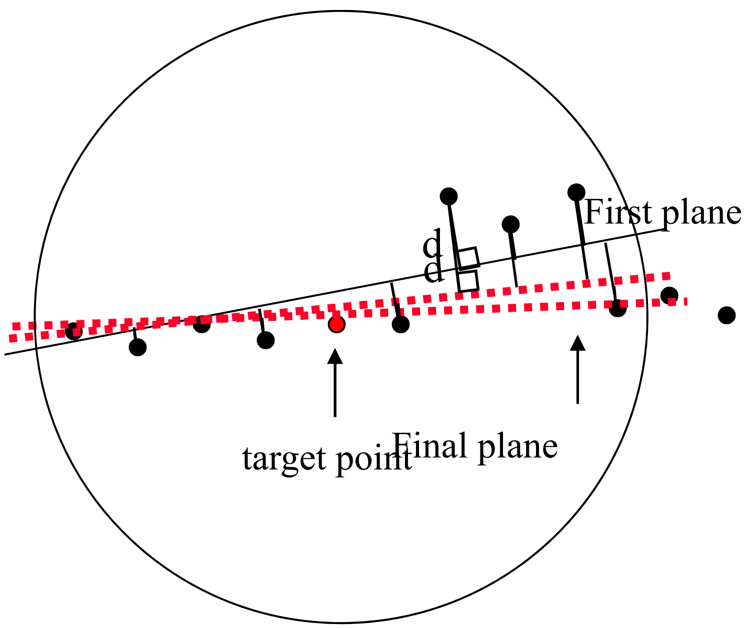
Neighborhood defined by adaptive cylinder

Neighborhood: Neighboring points that belong to the same physical surface.

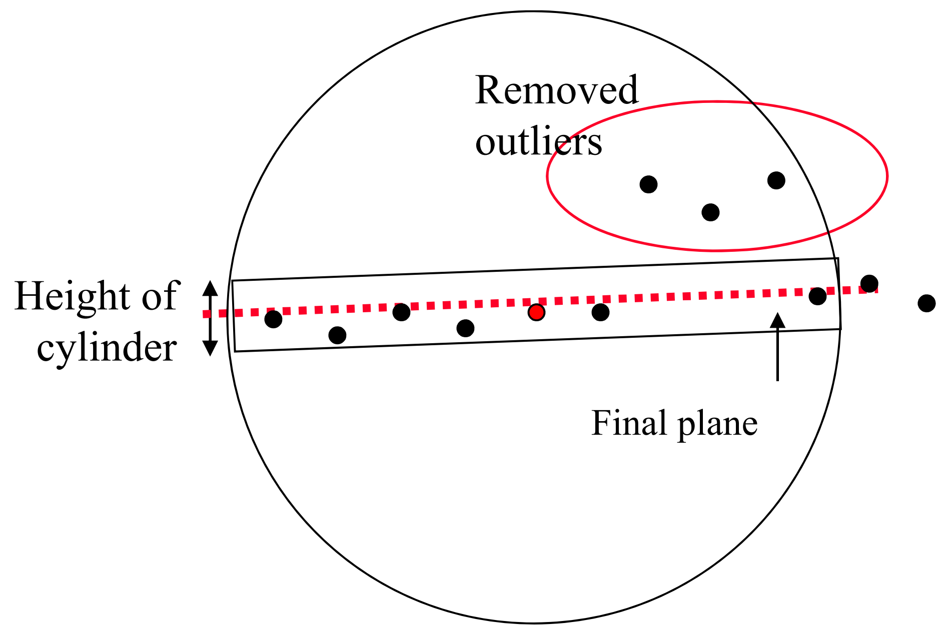
Neighborhood Definition

Adaptive Cylinder Derivation

Neighborhood defined by sphere

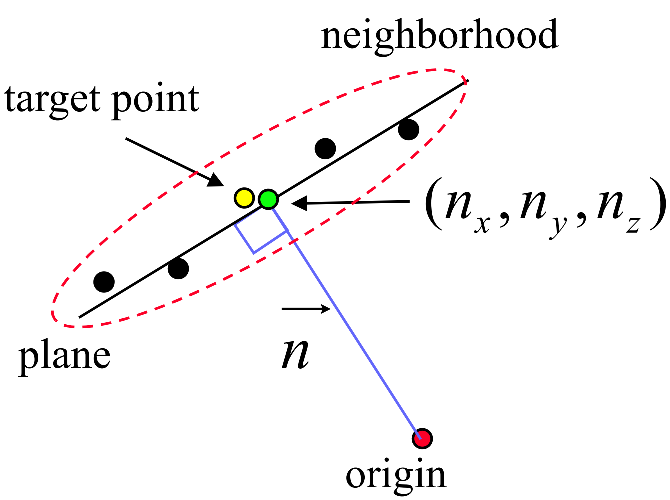


Neighborhood defined by adaptive cylinder

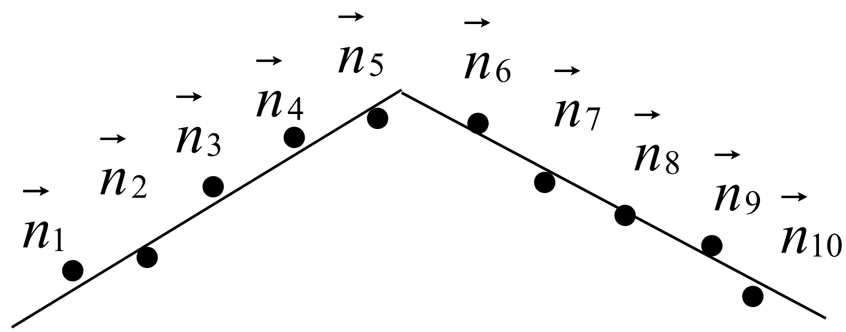


Attribute Evaluation

Planar patch attribute computation



$$n_x X + n_y Y + n_z Z = \left\|\vec{n}\right\|^2$$

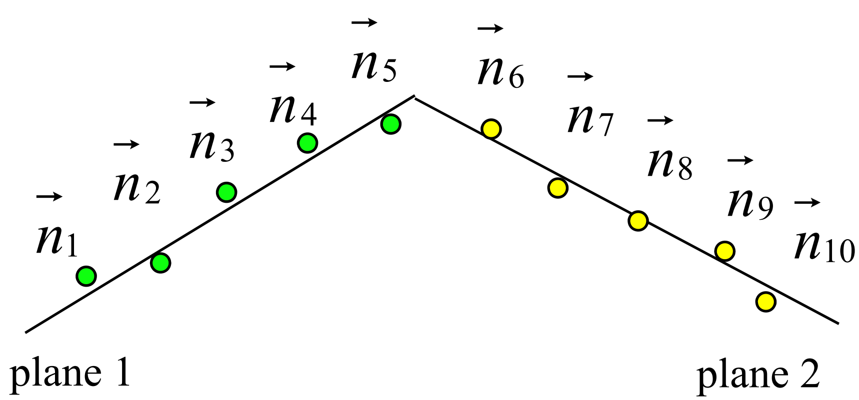


Each point i has its own vector, $\vec{n}_i$

Attribute Evaluation

Suitable Attributes

1. Normal vector components between a given origin and the planes defined by neighboring points using adaptive cylinder can be used as Attributes.
2. 4D accumulator array → computationally expensive.

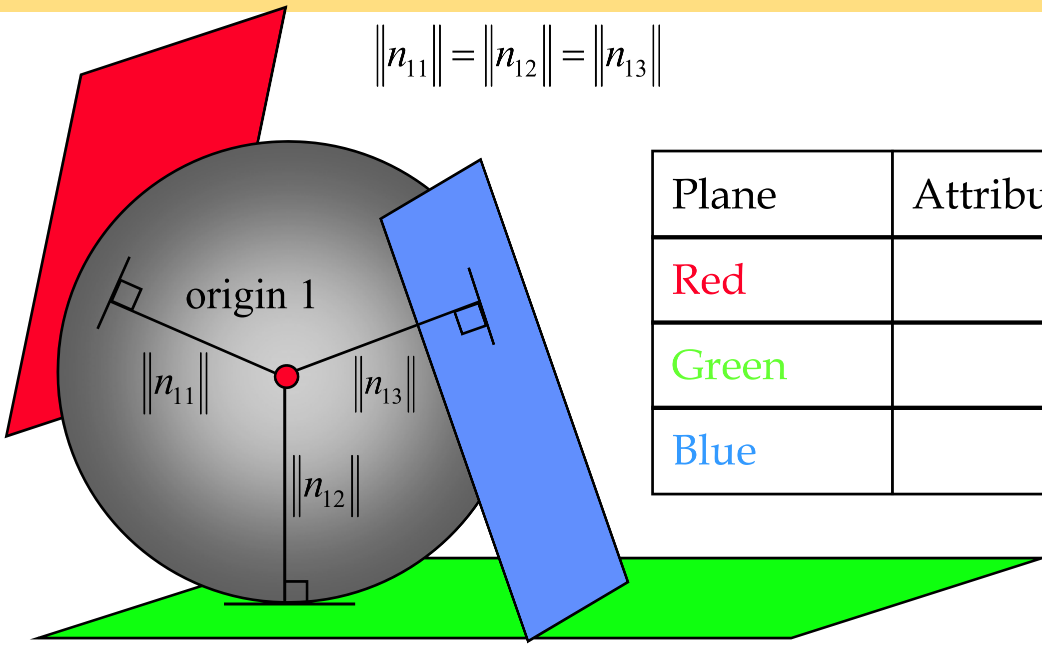


Attribute Evaluation

Suitable Attributes

1. Normal distances between a given origin and the planes defined by neighboring points using adaptive cylinder can be used as Attributes.
2. 2D accumulator array → quite convenient
3. Using only one origin might cause ambiguities in the derived attributes.

$$\|n_{11}\| = \|n_{12}\| = \|n_{13}\|$$

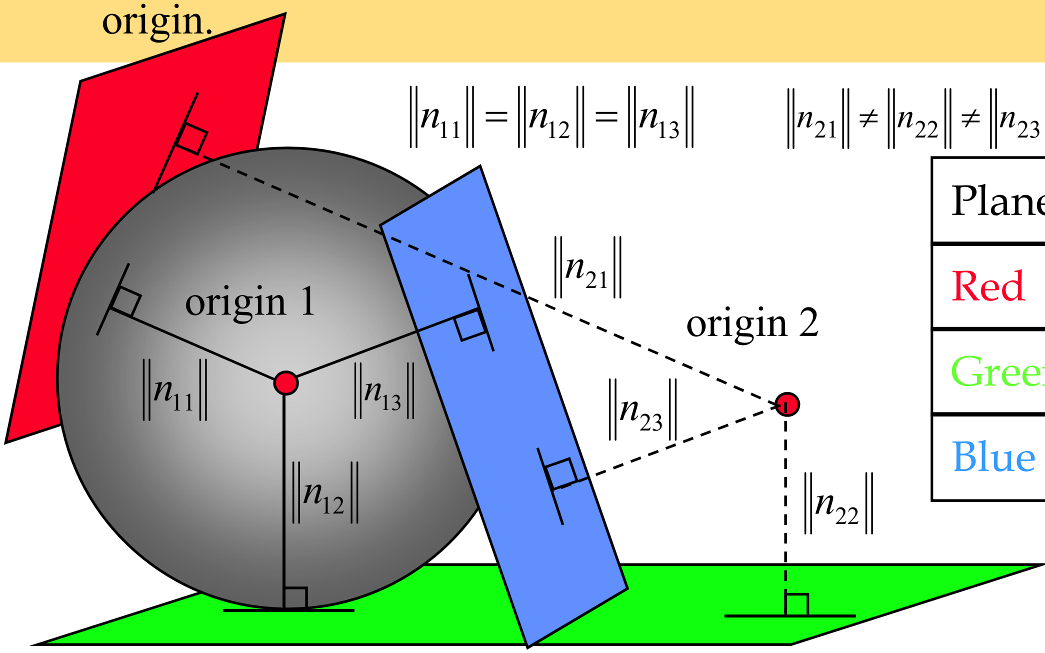


Plane	Attribute
Red	$\|n_{11}\|$
Green	$\|n_{12}\|$
Blue	$\|n_{13}\|$

Attribute Evaluation

Suitable Attributes

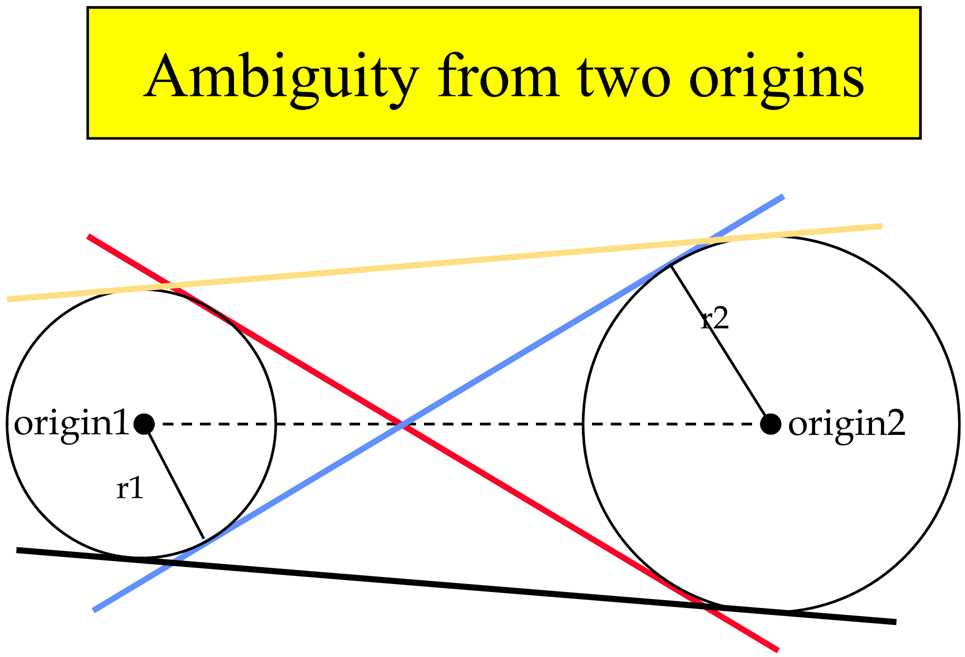
1. Normal distances between two origins and planes defined by neighboring points using adaptive cylinder are used as Attributes in this research.
2. 3D accumulator array → convenient
3. Using two origins can eliminate resulting ambiguities when using one origin.



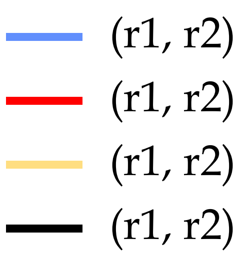
$$\|n_{11}\| = \|n_{12}\| = \|n_{13}\| \qquad \|n_{21}\| \neq \|n_{22}\| \neq \|n_{23}\|$$

Plane	Attribute	
Red	$\|n_{11}\|$	$\|n_{21}\|$
Green	$\|n_{12}\|$	$\|n_{22}\|$
Blue	$\|n_{13}\|$	$\|n_{23}\|$

Attribute Evaluation

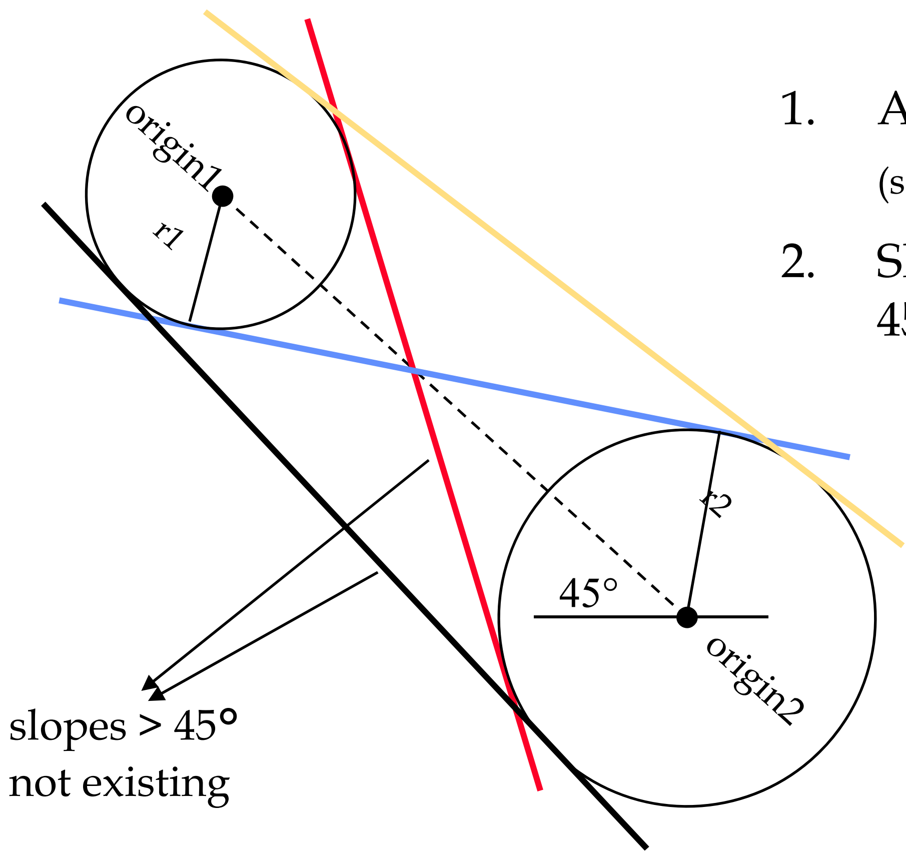


coordinates in the accumulator array



Attribute Evaluation

Ambiguity from two origins

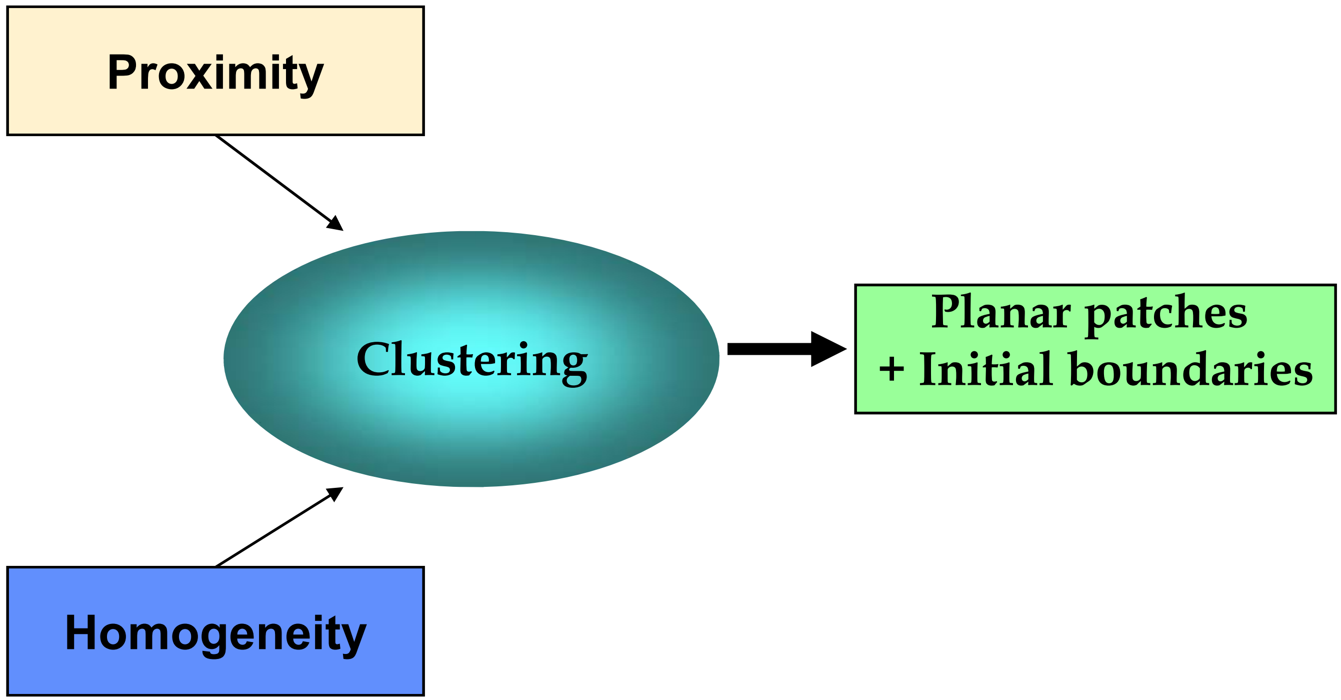


1. Assumption: slopes of building roofs < 45°

   (since most building roofs are flat or gently sloped)

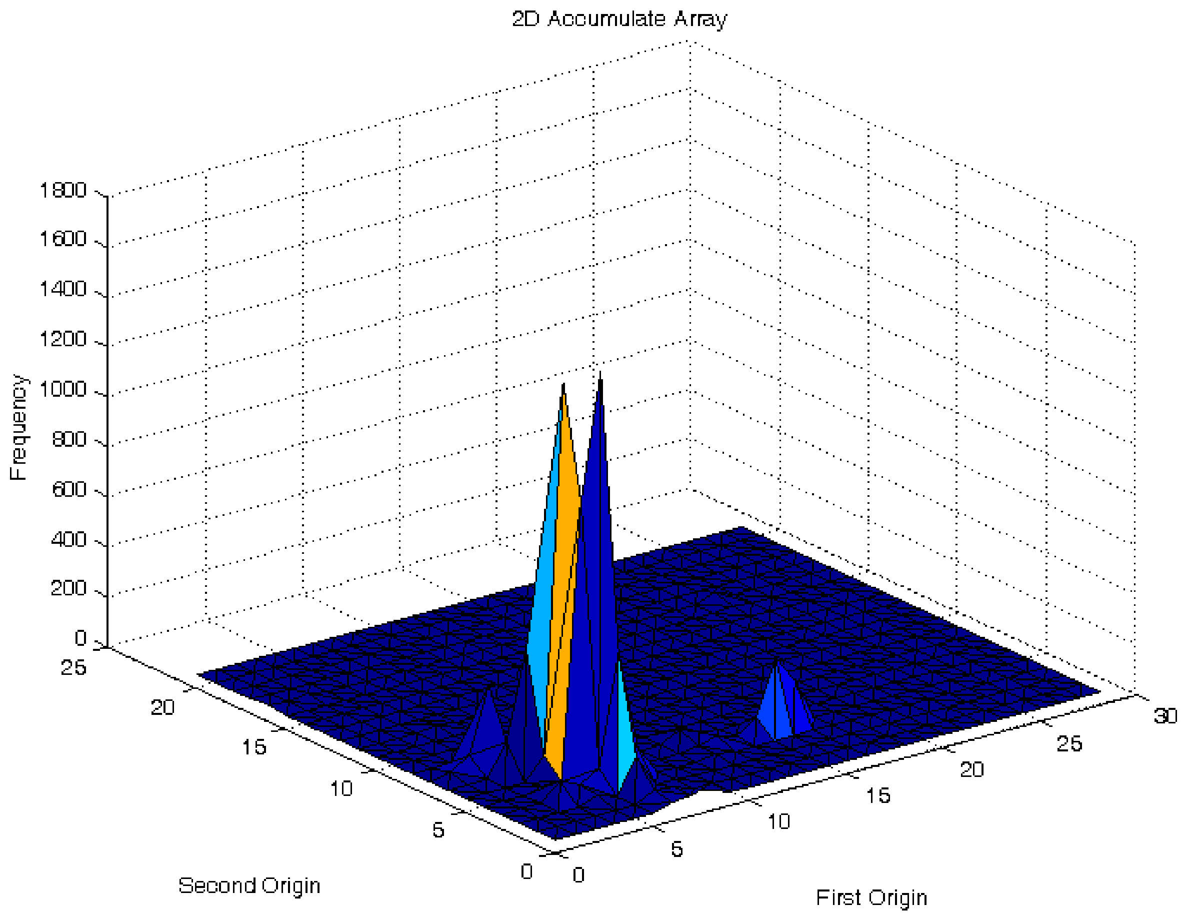
2. Slope of a line connecting two origins = 45°

Clustering



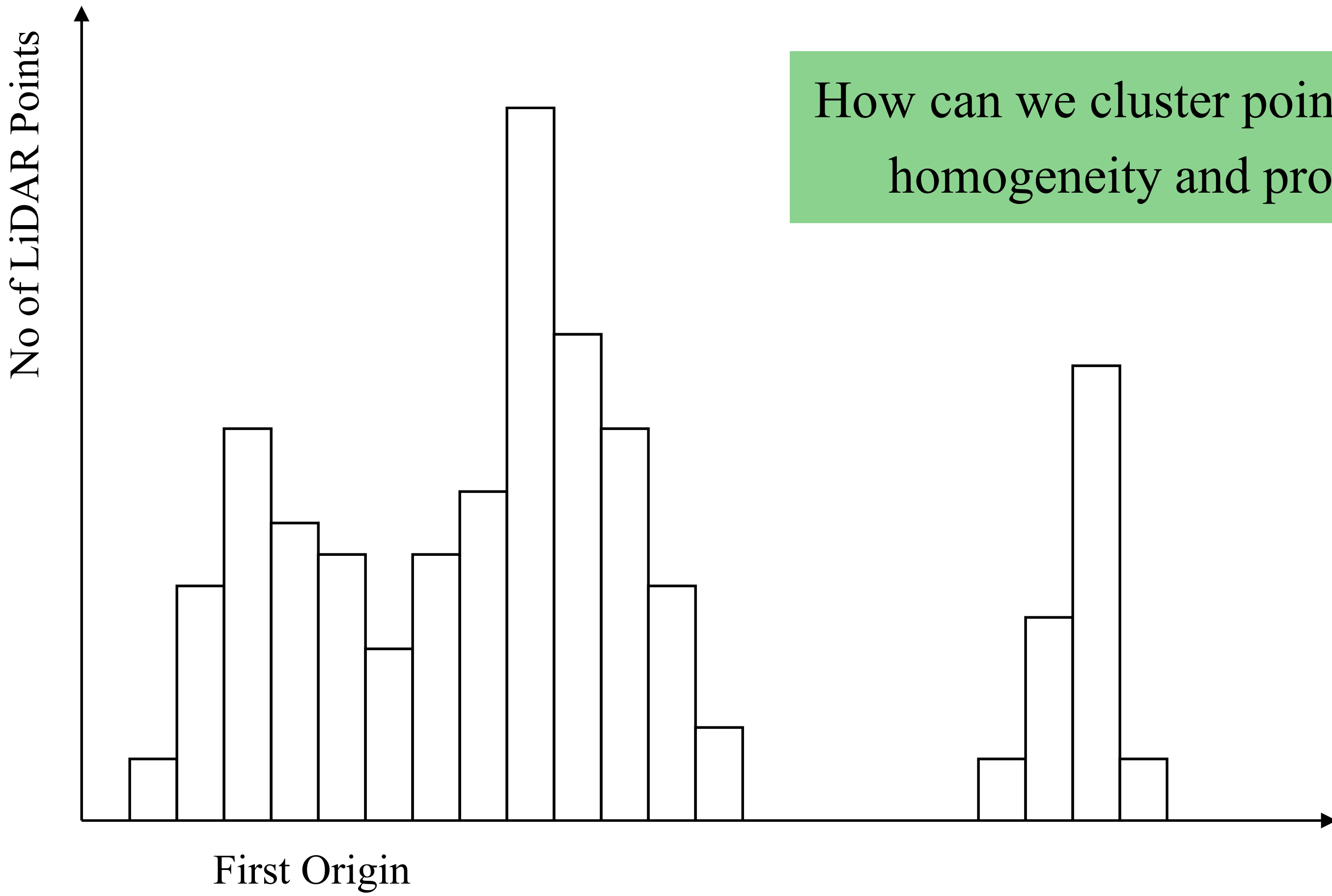
Simultaneously considering Homogeneity (globally) in the parameter space + Proximity (locally) in the object space → Accurate & Robust solution

Clustering



Accumulator Array

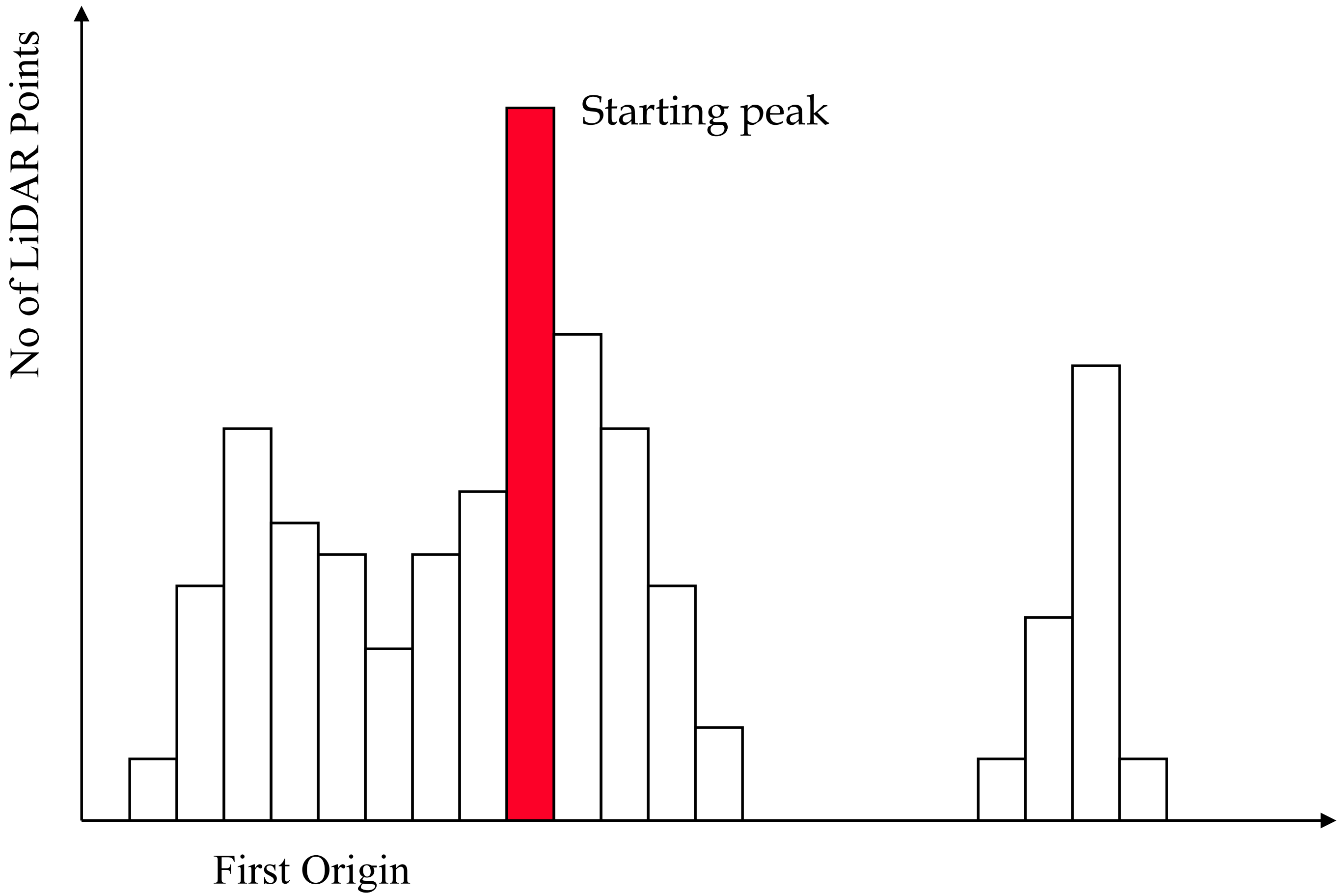
Clustering



How can we cluster points based on homogeneity and proximity?

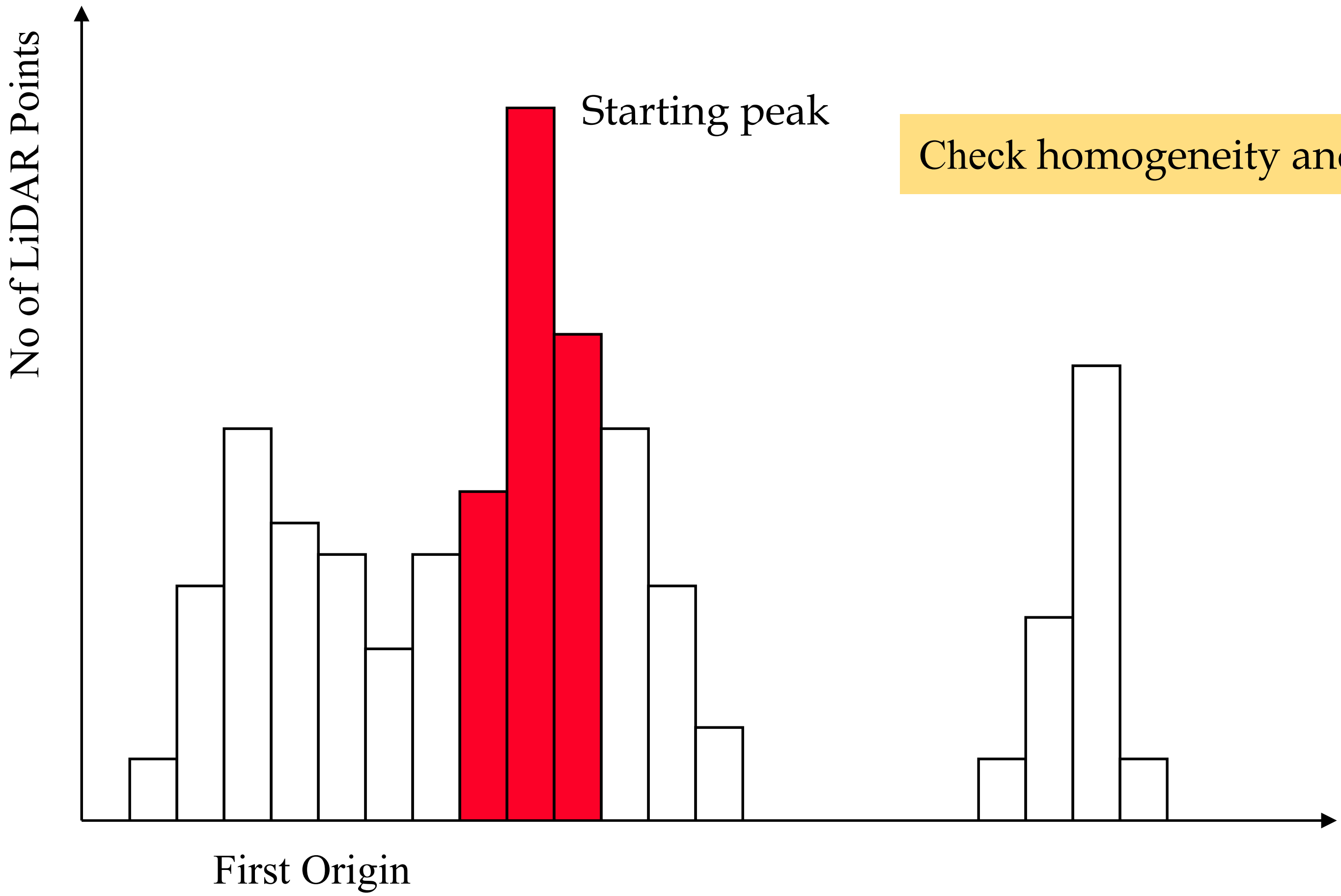
Accumulator Array (Side View)

Clustering



Accumulator Array (Side View)

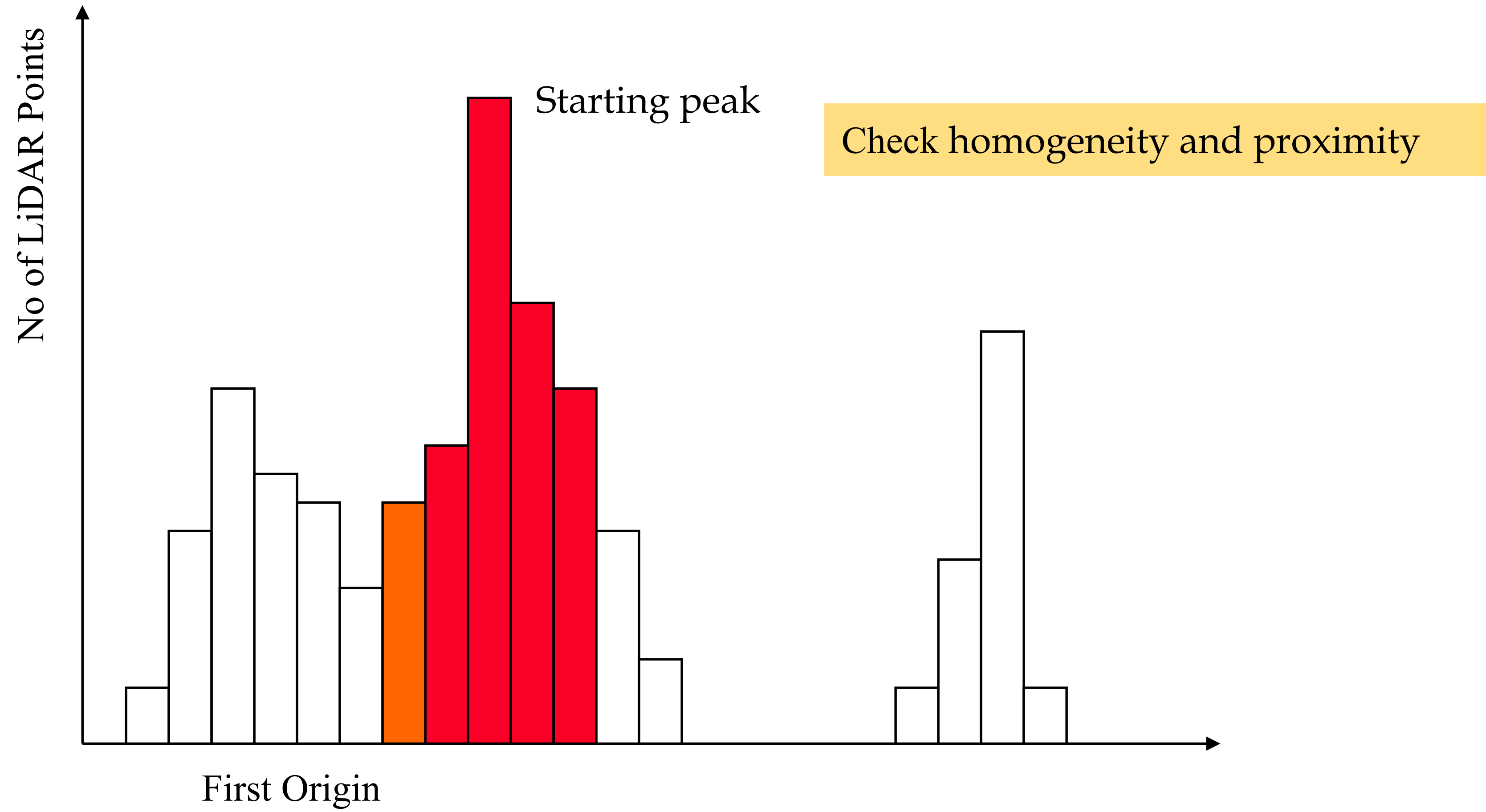
Clustering



Check homogeneity and proximity

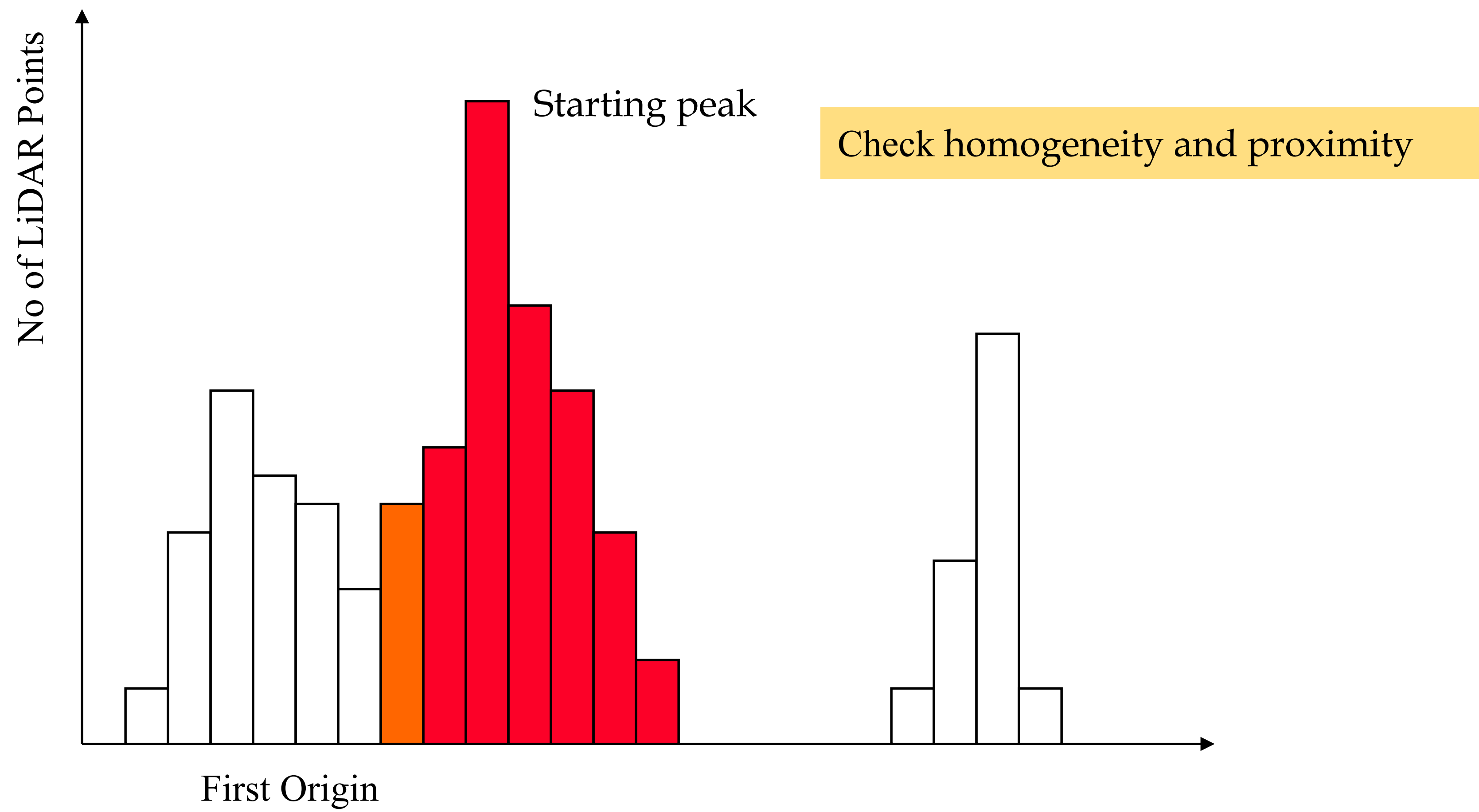
Accumulator Array (Side View)

Clustering



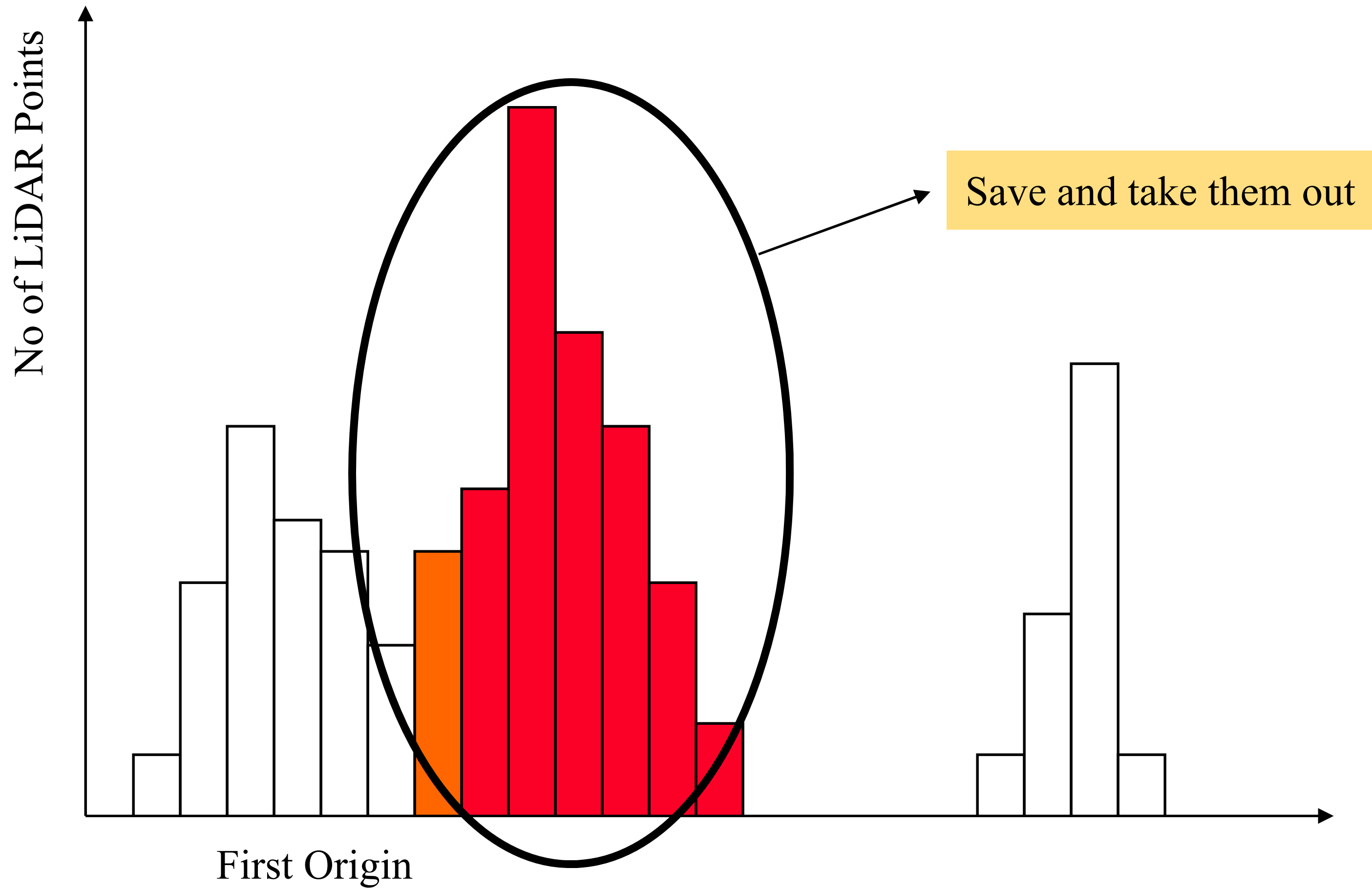
Accumulator Array (Side View)

Clustering



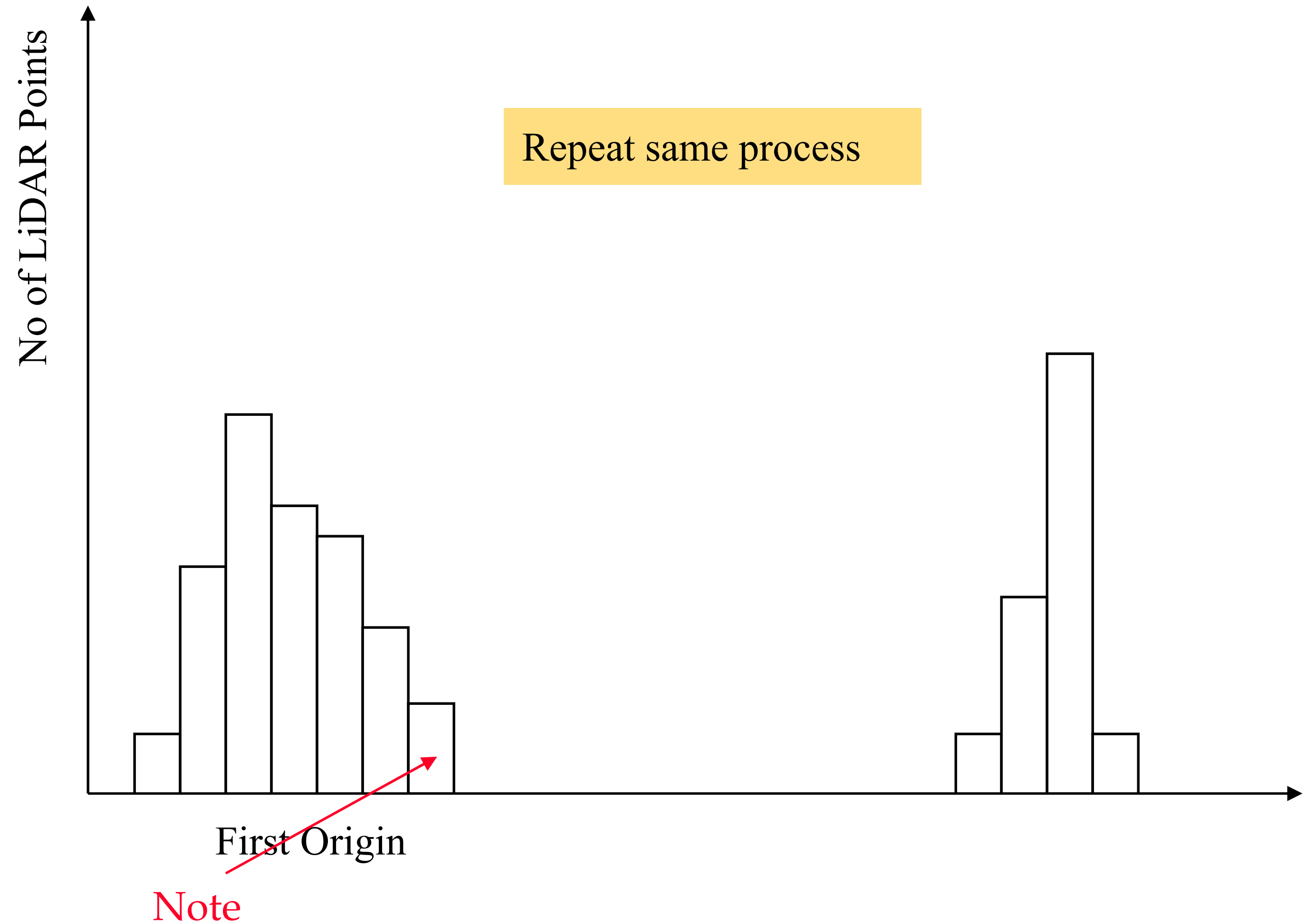
Accumulator Array (Side View)

Clustering



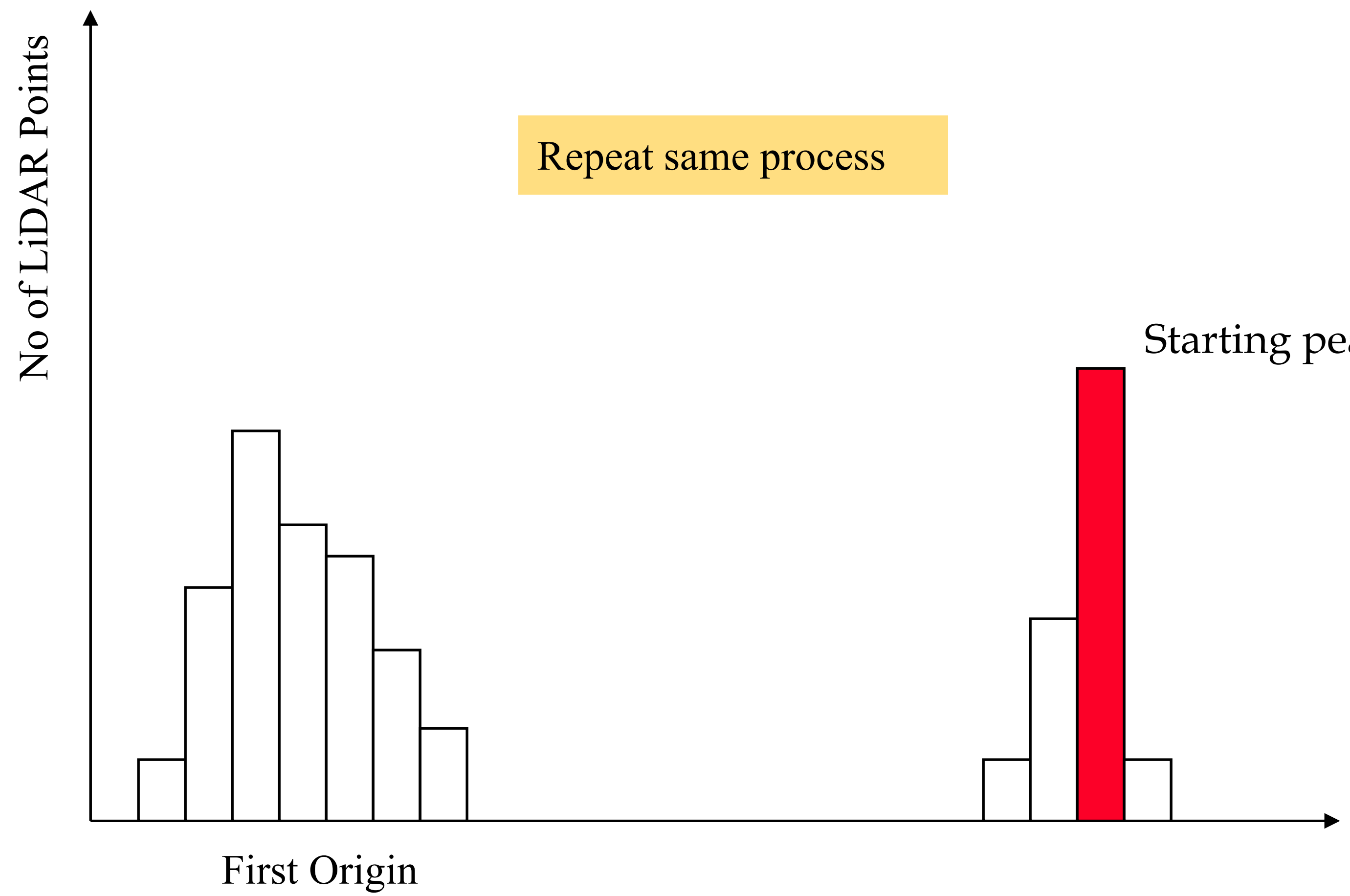
Accumulator Array (Side View)

Clustering



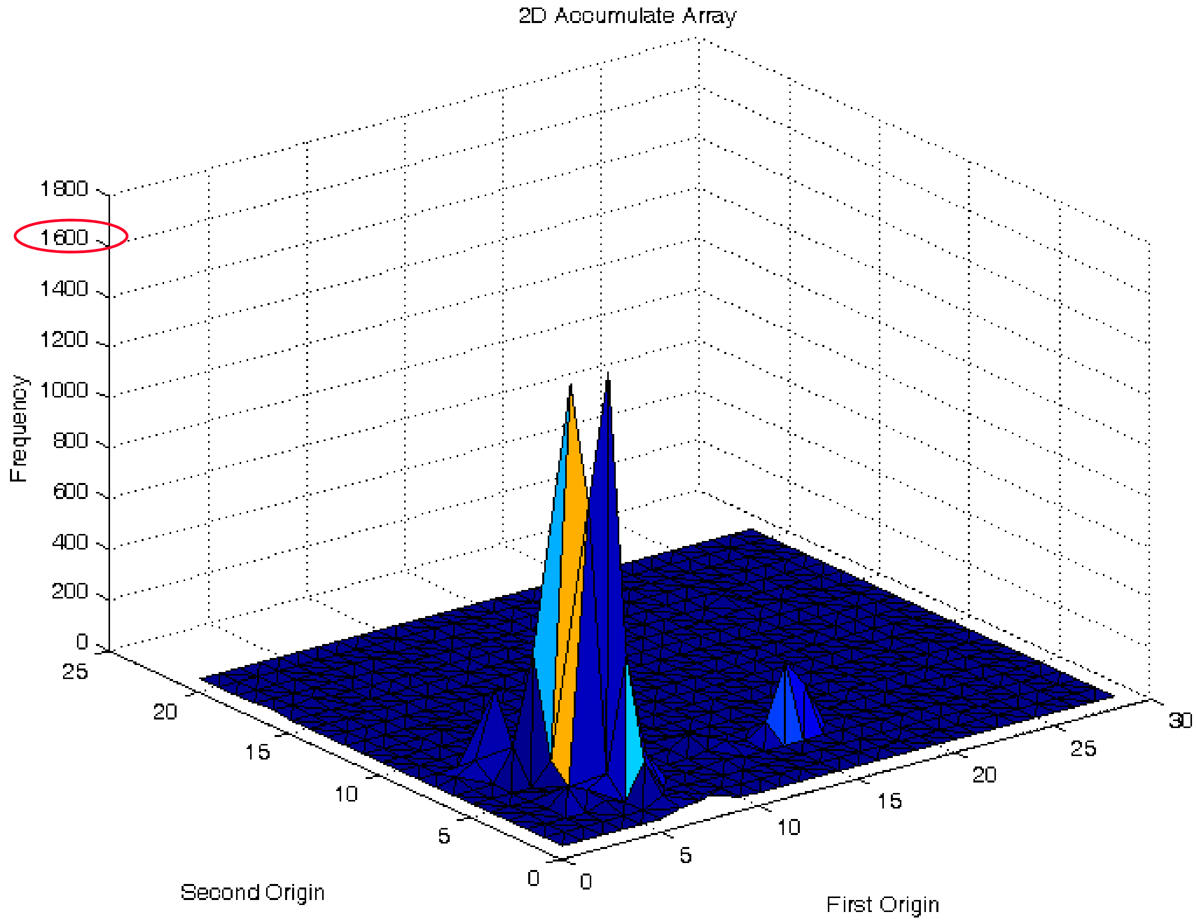
Accumulator Array (Side View)

Clustering



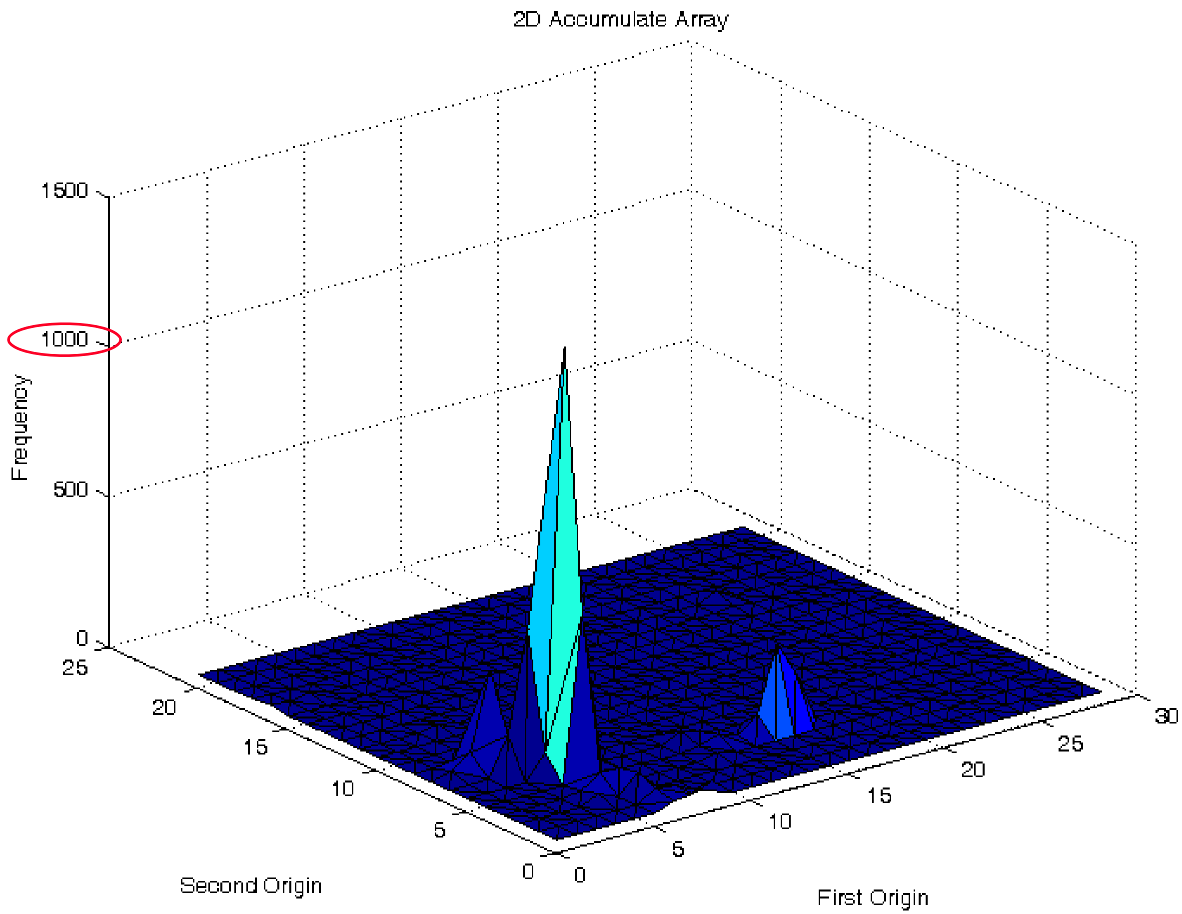
Accumulator Array (Side View)

Clustering



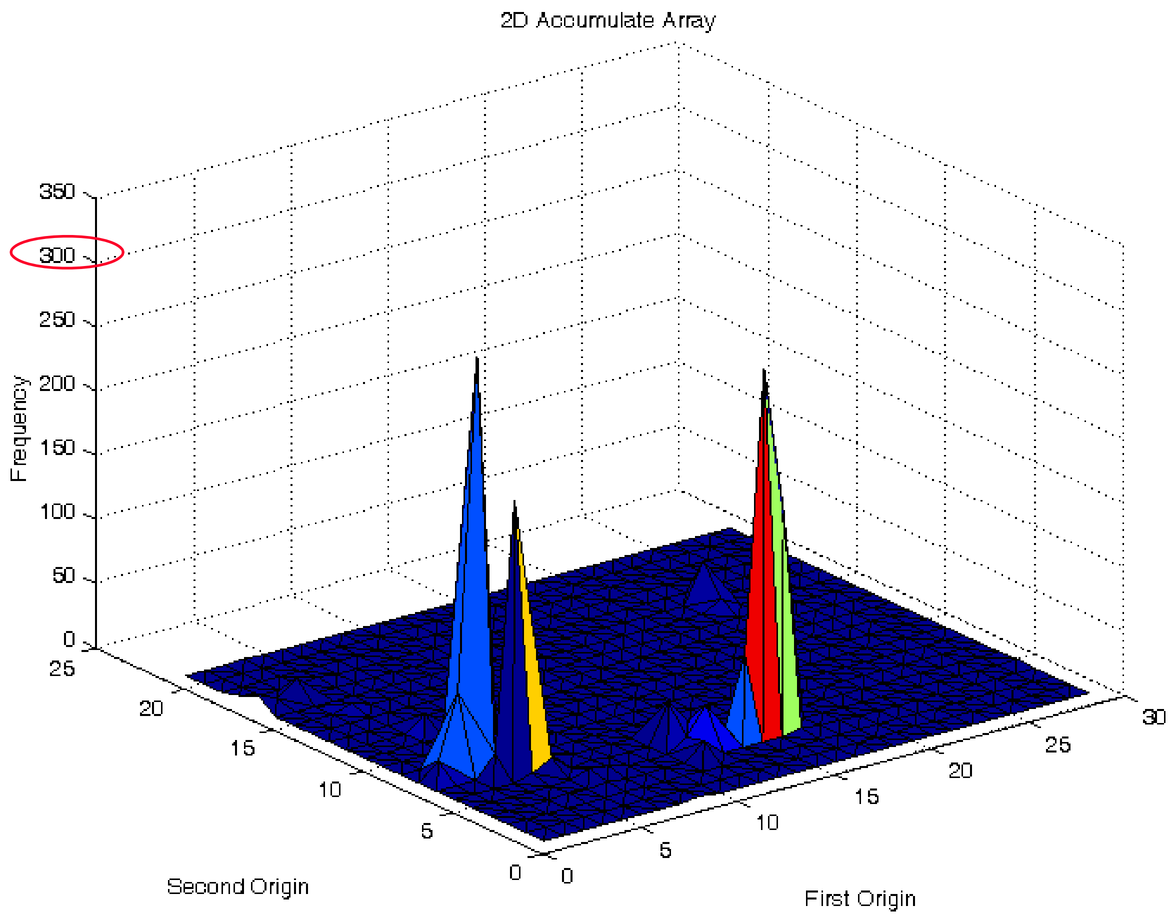
Accumulator Array

Clustering



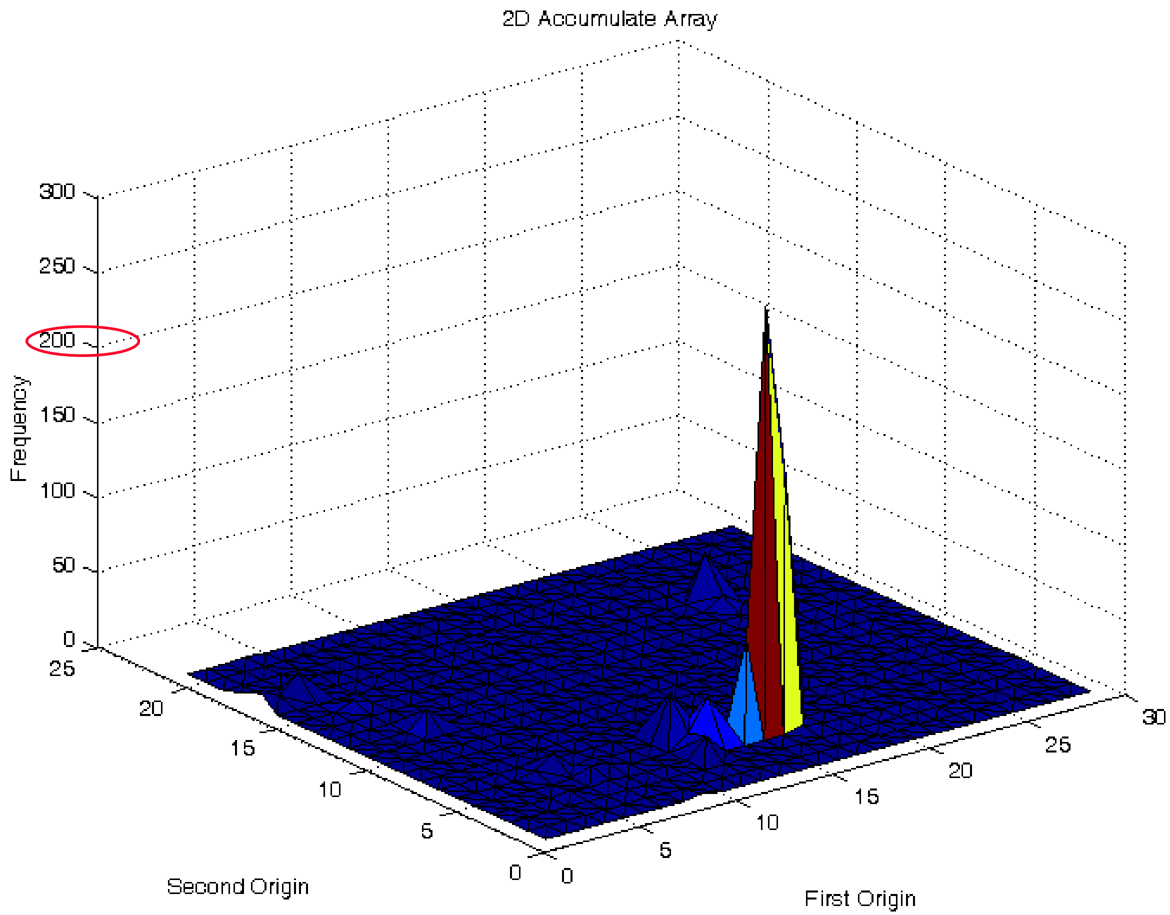
Accumulator Array after Removing the First Cluster

Clustering



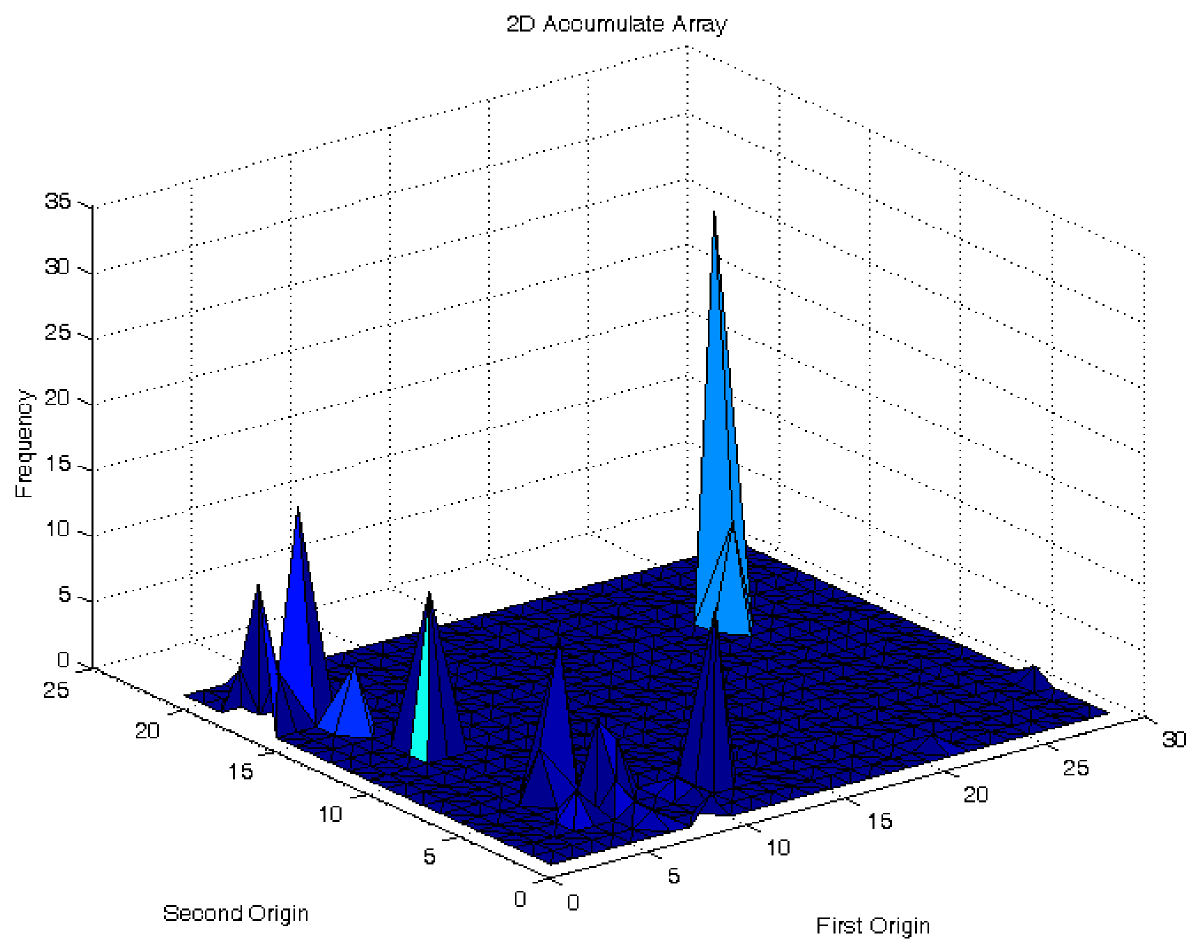
Accumulator Array after Removing the Second Cluster

Clustering



Accumulator Array after Removing the Third Cluster

Clustering

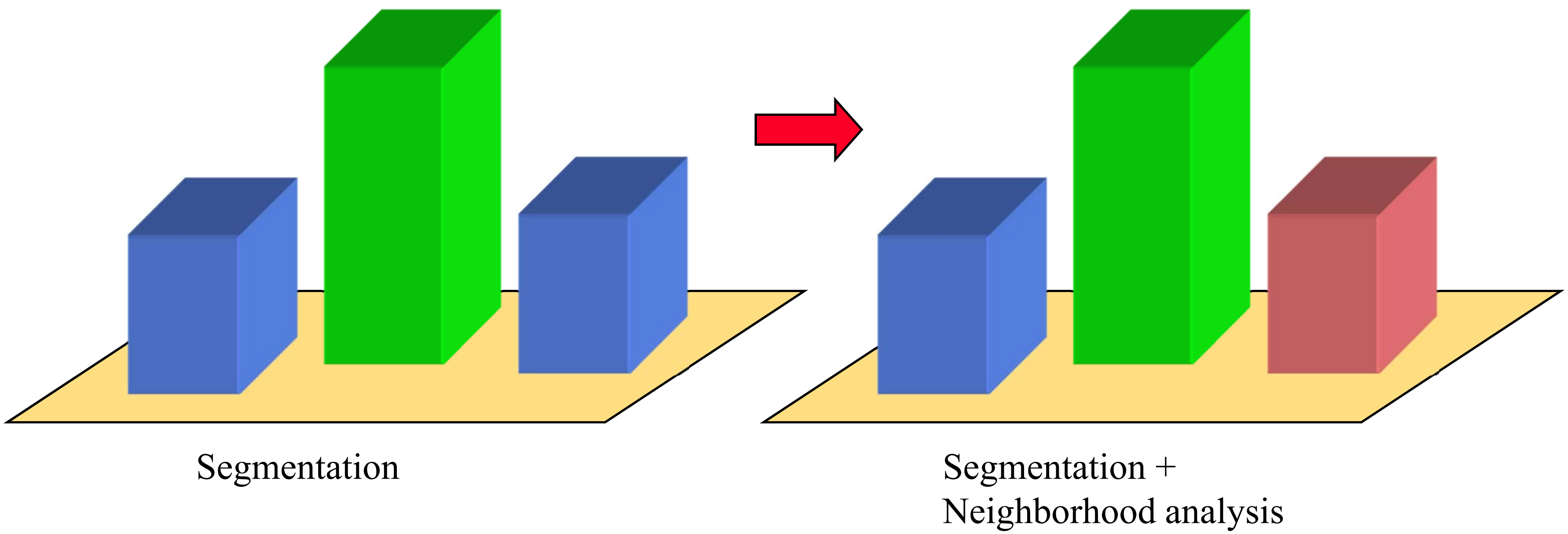


Accumulator Array after Removing the Fourth Cluster

Clustering

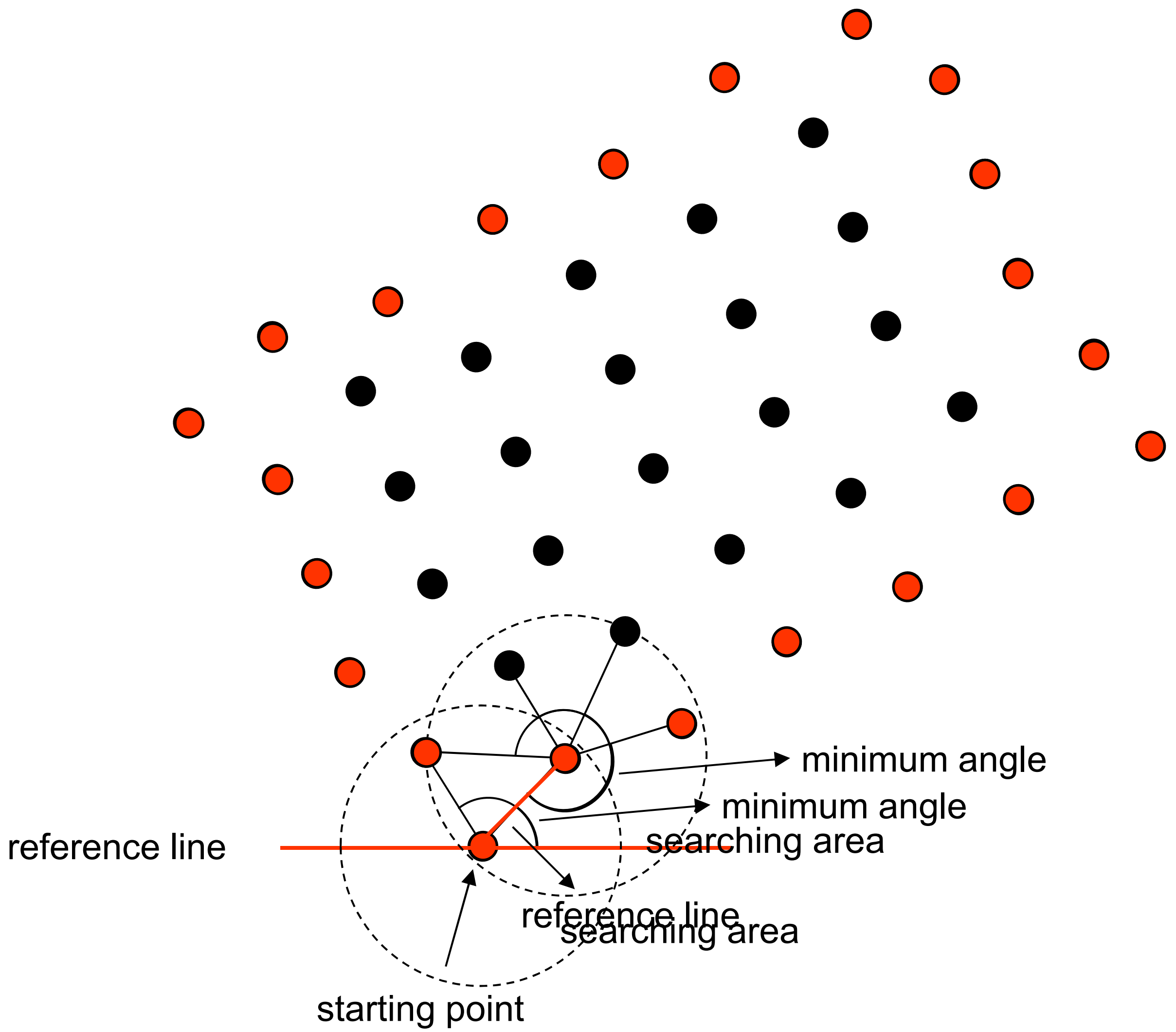
Boundary Detection

Ambiguity Resolution: Neighborhood analysis using boundary detection



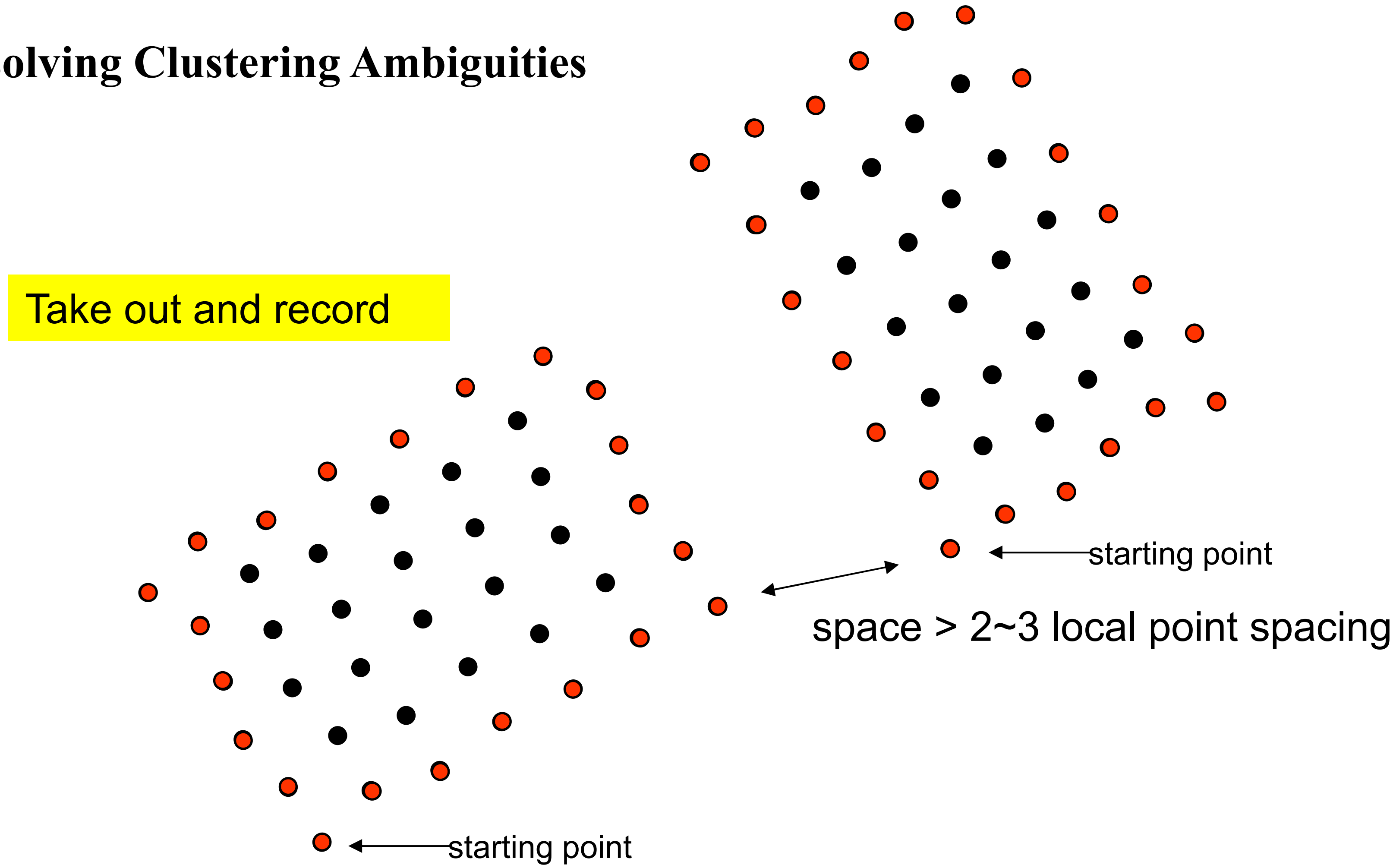
Boundary Detection

Modified/Minimum Convex Hull Procedure



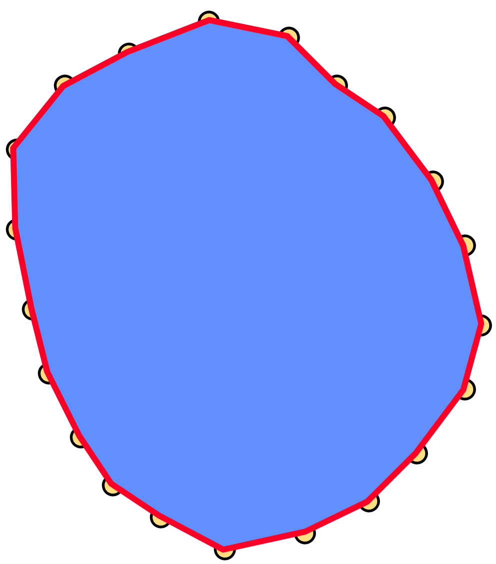
Boundary Detection

Resolving Clustering Ambiguities



Neighborhood analysis is conducted through boundary detection

Boundary Expansion



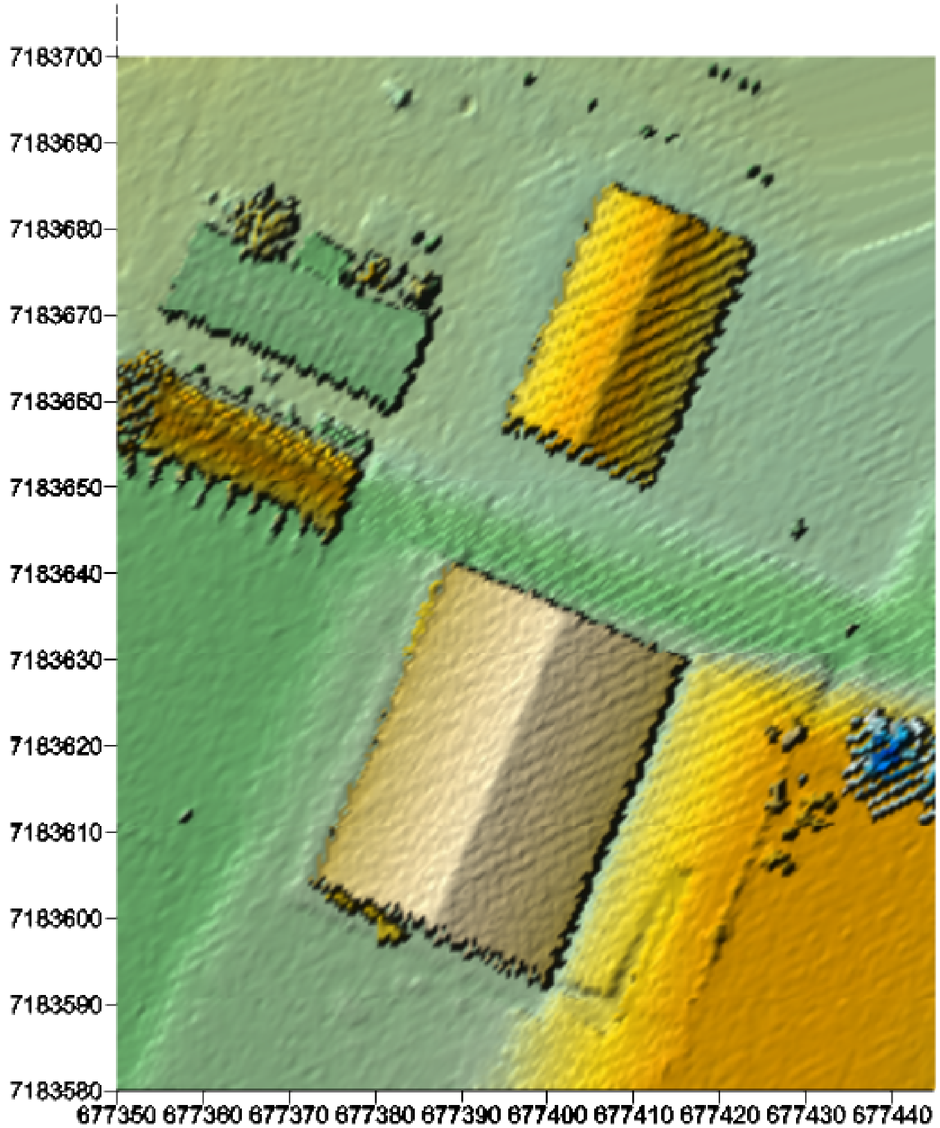
Boundaries are expanded while checking normal distances between candidate points and the defined plane

● segmented points

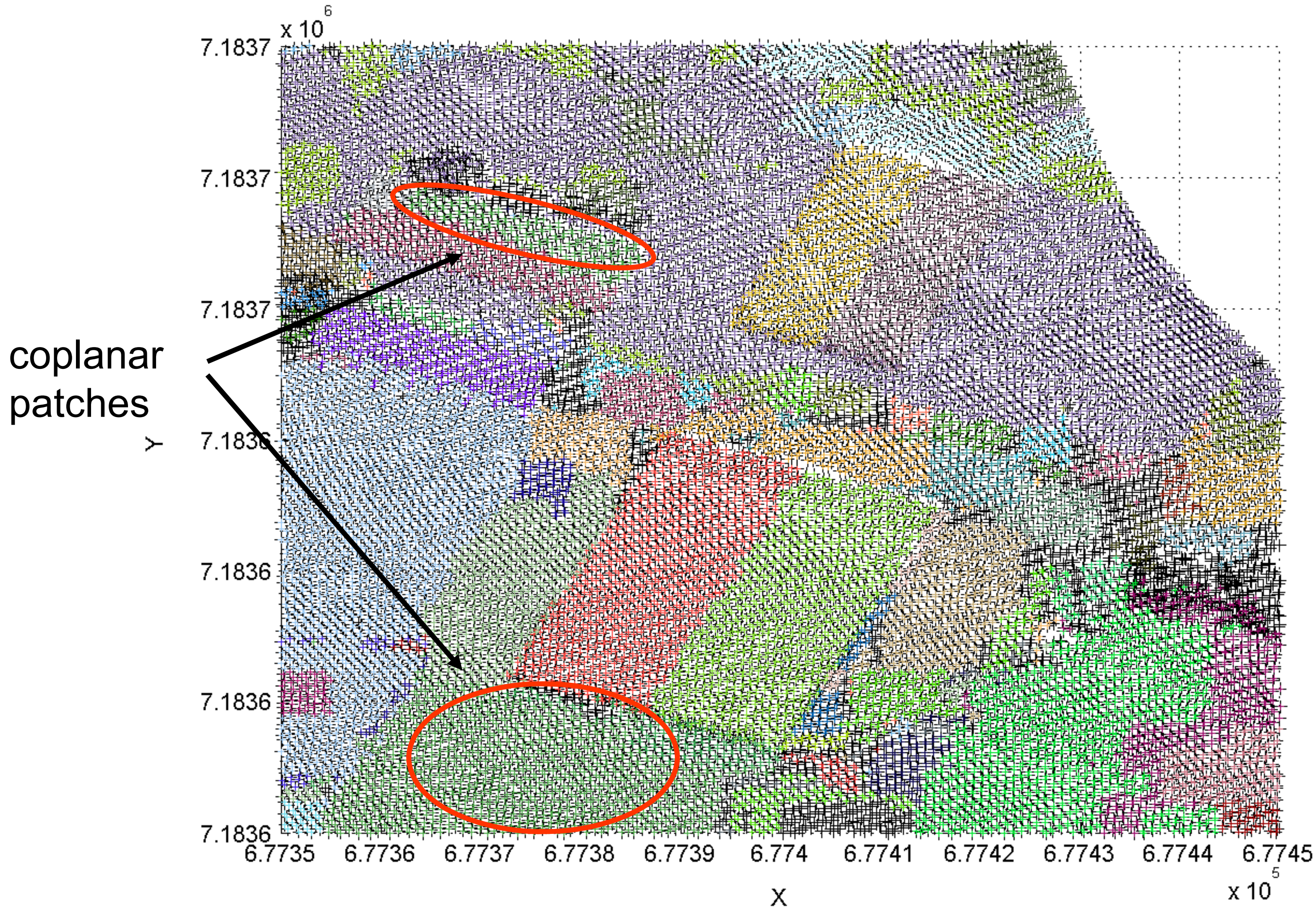
○ non-segmented points

Segmentation Example (Imagery)

Segmentation Example (LiDAR)



Segmentation Example: Output



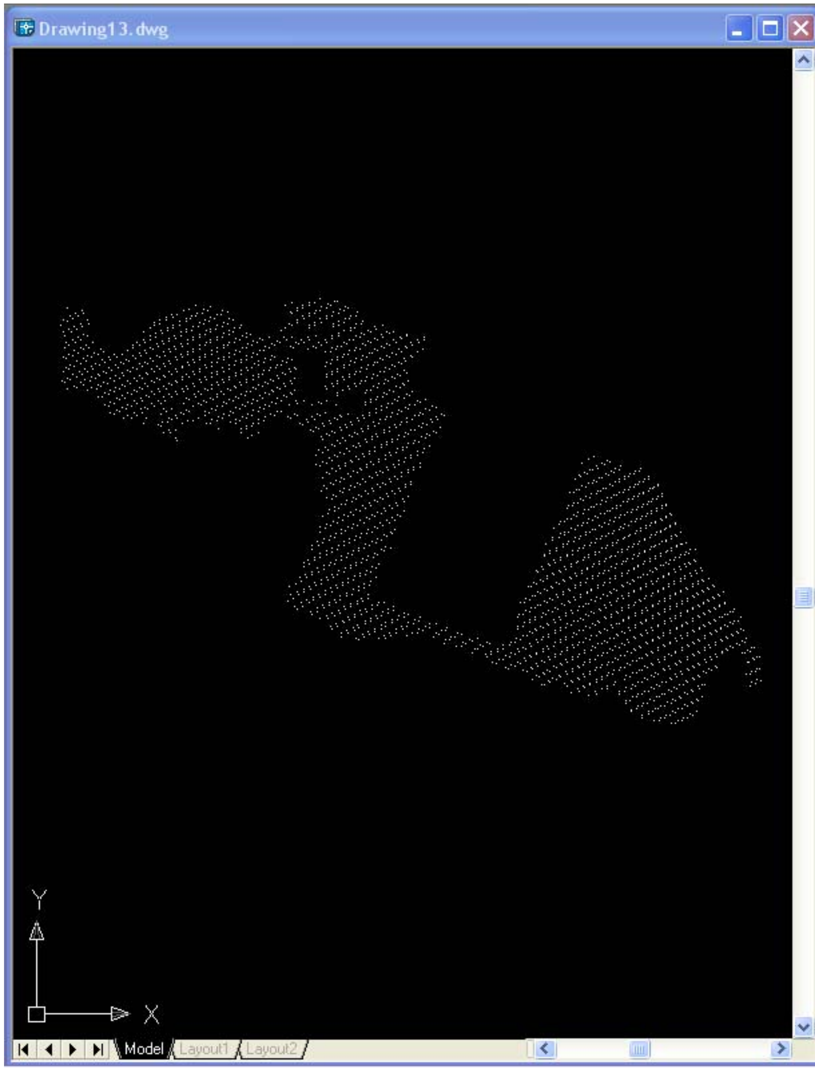
Segmentation Example: Output

Before expanding boundaries

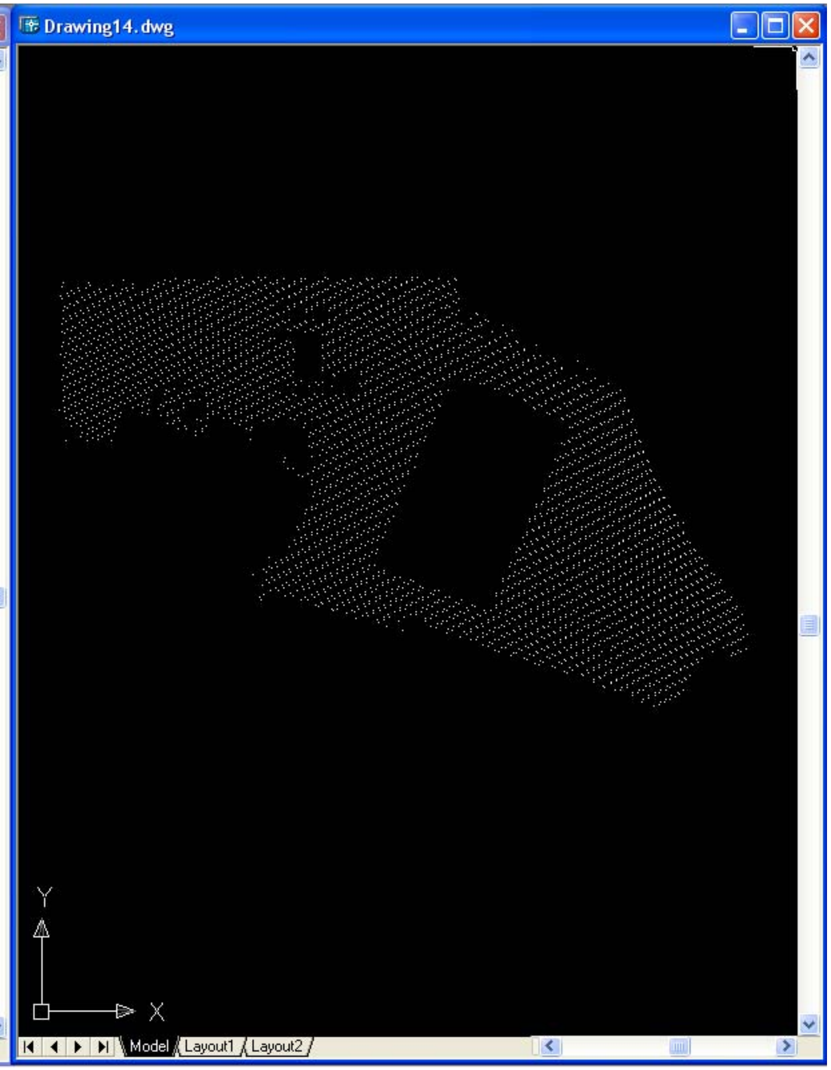
Segmentation Example: Output

After expanding
boundaries – no tail

Boundary Expansion



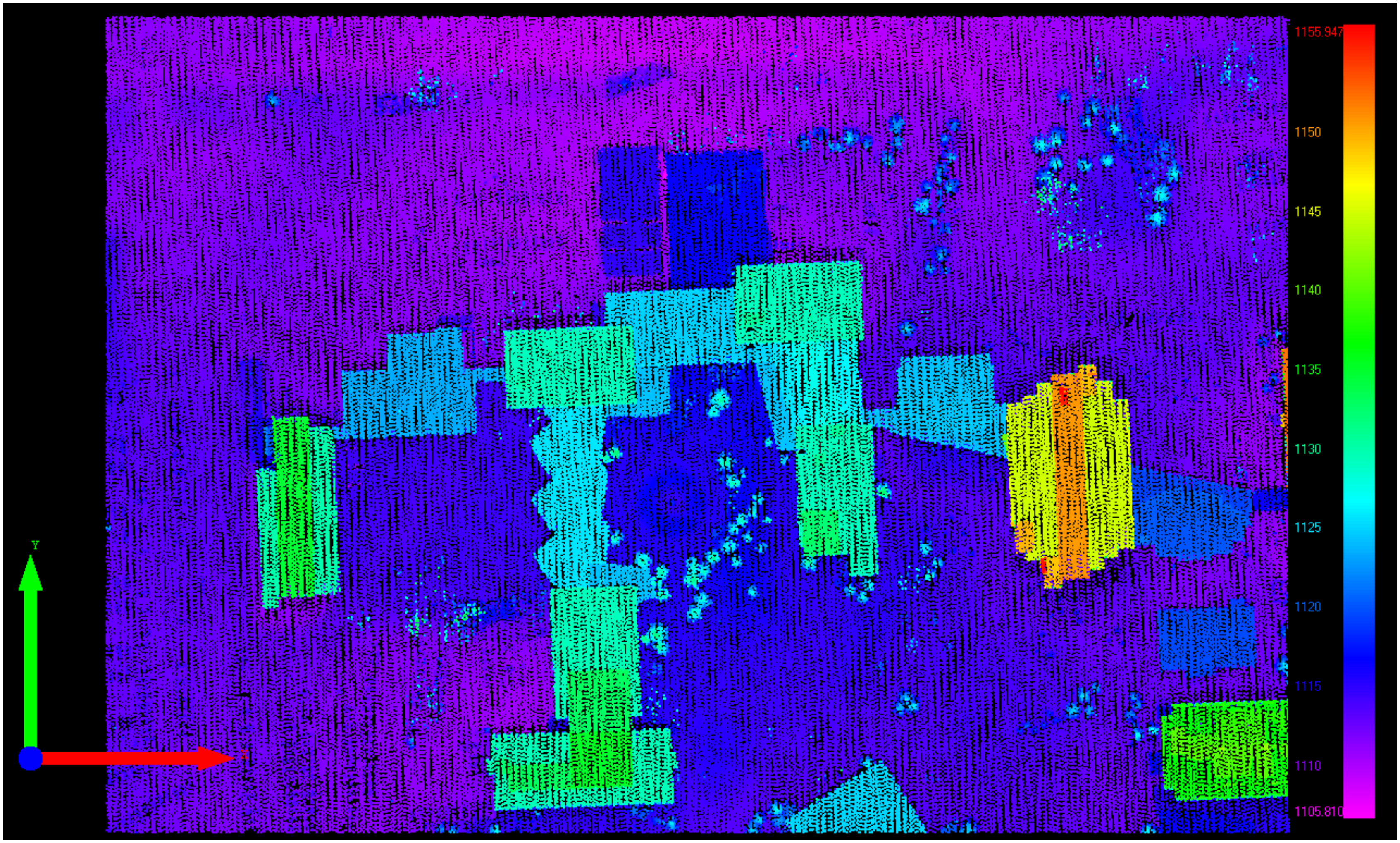
Before expanding



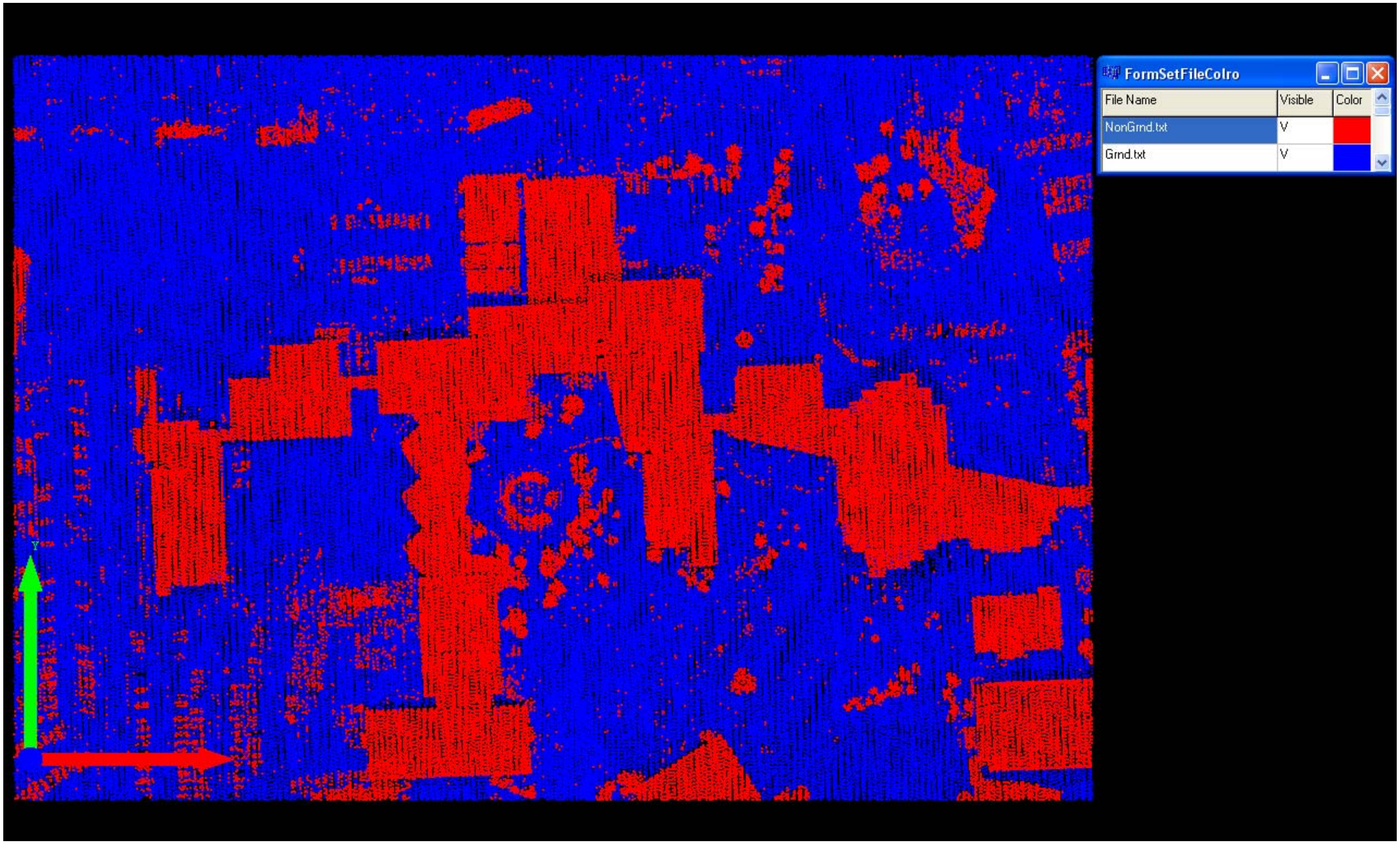
After expanding

Aerial Photo

Original LiDAR Points



Ground/Non-Ground Classification



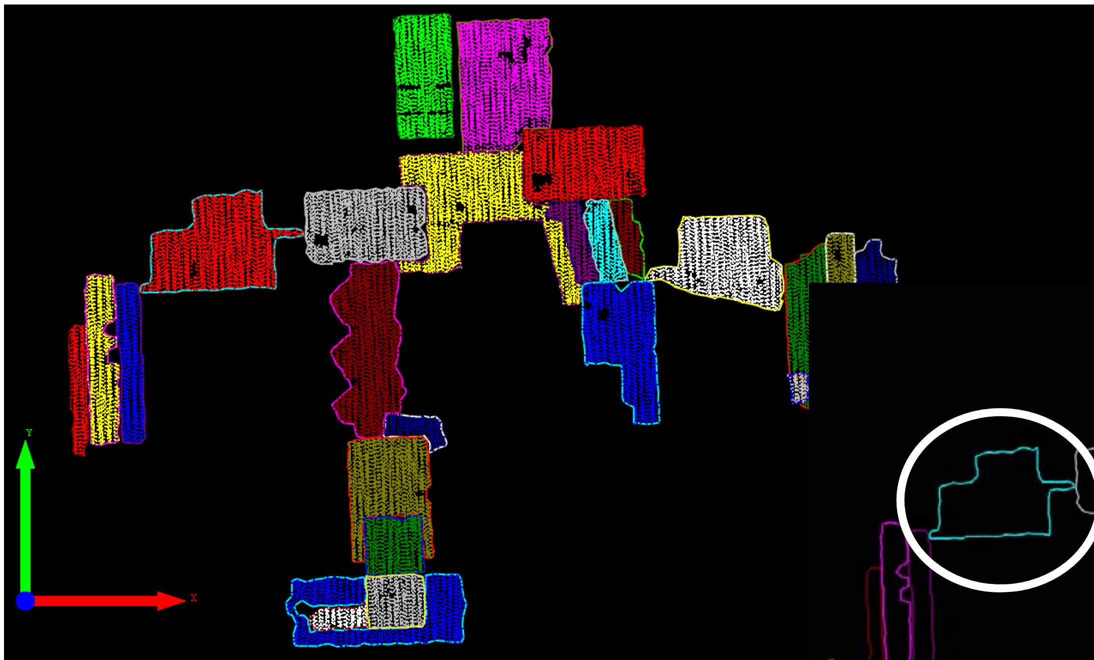
Ground/Non-Ground Points

Segmentation Results

Boundaries of Segmented Patches

Resolves the ambiguity arising from having spatially separated but coplanar patches

Segmentation Results



Segmentation + Initial boundaries

Initial boundary

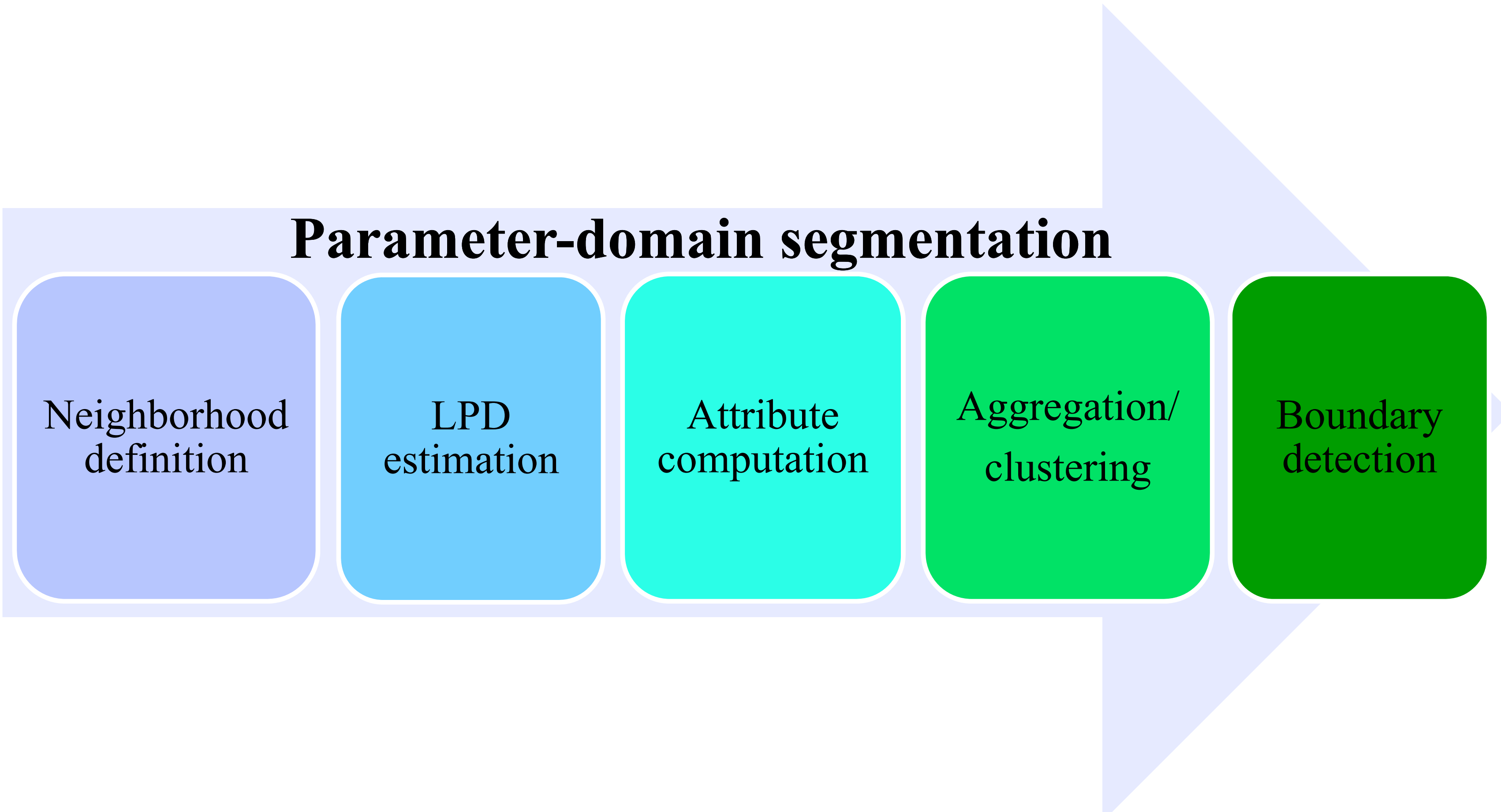
Segmentation Results

Projected LiDAR boundary on an aerial photo

Parameter-Domain Segmentation

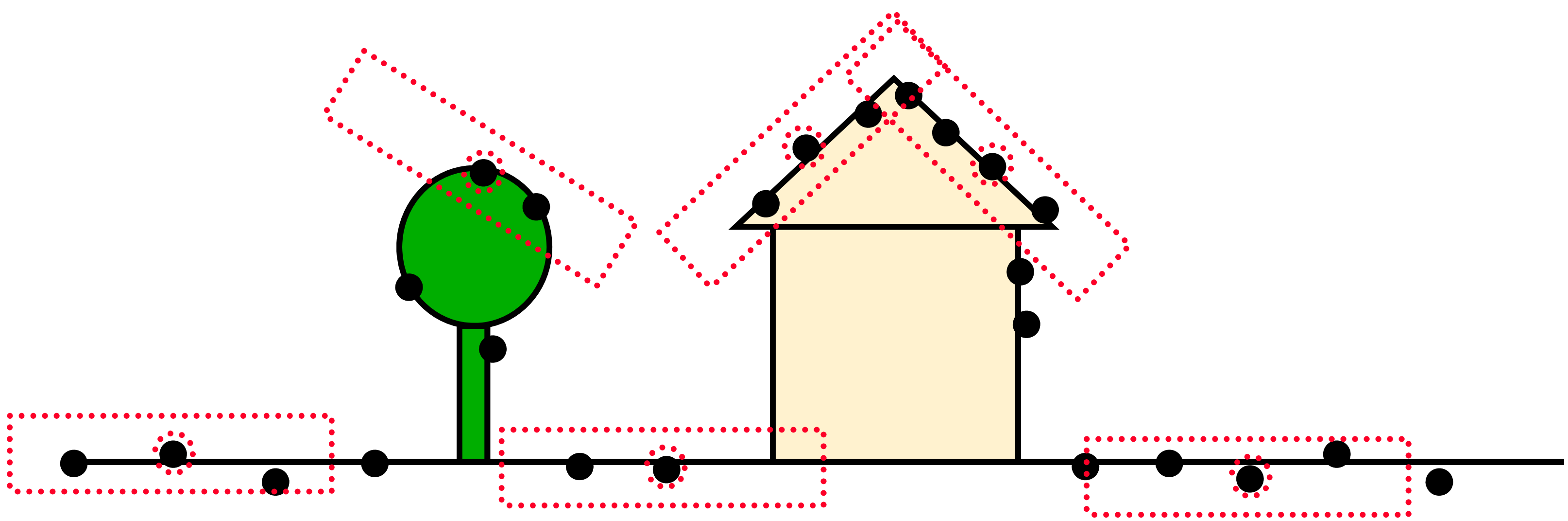
Alternative Approach

Parameter-Domain Segmentation



Parameter-Domain Segmentation

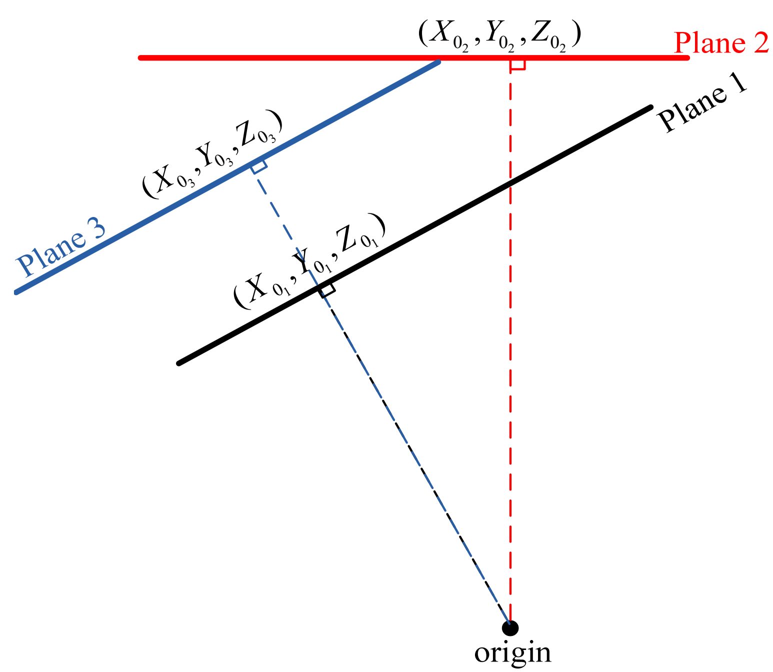
- **Neighborhood Definition:** A rule that determines the neighbors of each point.
  - This definition significantly affects the validity of computed attributes for laser point cloud segmentation.



Neighborhood defined by adaptive cylinder

Parameter-Domain Segmentation

- **Attribute computation:** Estimation of criteria which are used for measuring the similarity among a group of points in order to abstract the laser point cloud into distinct subsets of points
- **Utilized attributes in this research:** the coordinates of origin's projection on the best fitting plane to each point's 3D neighborhood (X_0, Y_0, Z_0) derived through adaptive cylinder definition.



Clustering – Peak Detection

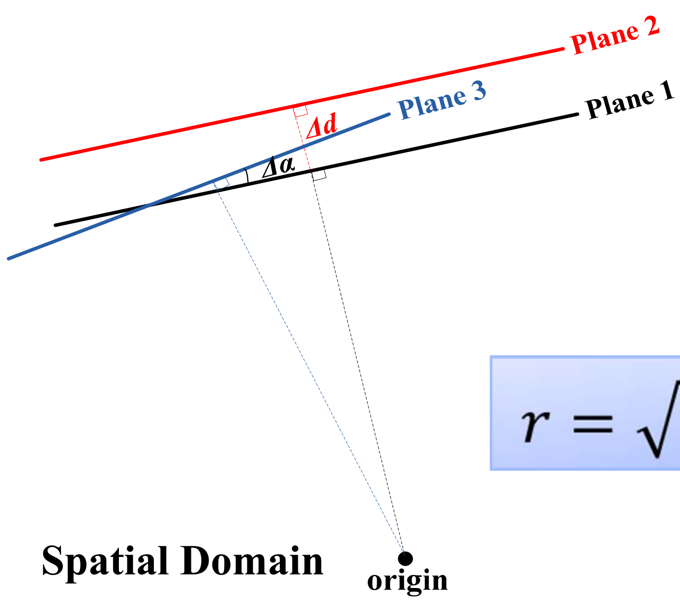
- Usually, cluster detection is carried out using a tessellated accumulator array in the parameter/attribute space.
  - The quality of the segmentation outcome depends on the cell size of the tessellation.
  - To avoid this problem, we introduce **two different methods** for peak detection in the attribute space:
    - Brute-force approach for peak detection
    - Fast approach for peak detection: An octree space partitioning for **coarse detection** followed by a **fine detection** of the peak.
- For either method, we need to specify the expected spread of the cluster in the attribute space (acceptable spatial and angular deviation among the attributes of the points in a given cluster).

Parameter-Domain Segmentation

- **Determination of expected cluster extent in attribute space**

The impact of Δα and Δd on the cluster extent:

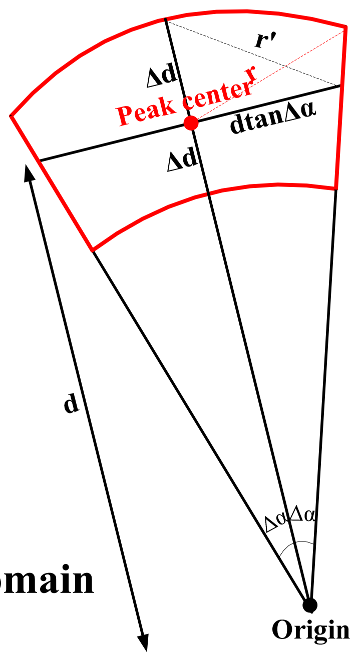
Δα	Acceptable angular deviation between two planes that should be clustered as one plane
Δd	Acceptable spatial separation between two parallel planes that should be clustered as one plane



Spatial Domain

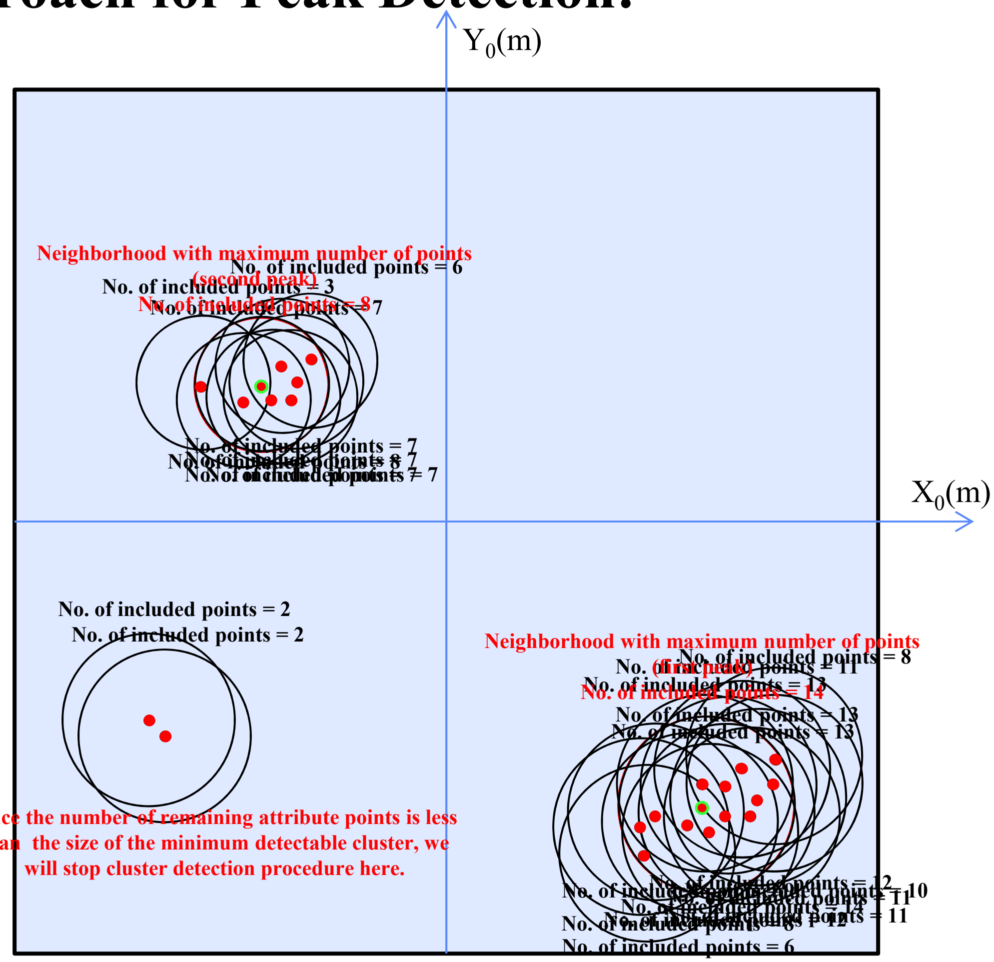
$$r = \sqrt{(d\tan \Delta\alpha)^2 + (\Delta d)^2}$$

Parameter Domain



Parameter-Domain Segmentation

Brute-force Approach for Peak Detection:

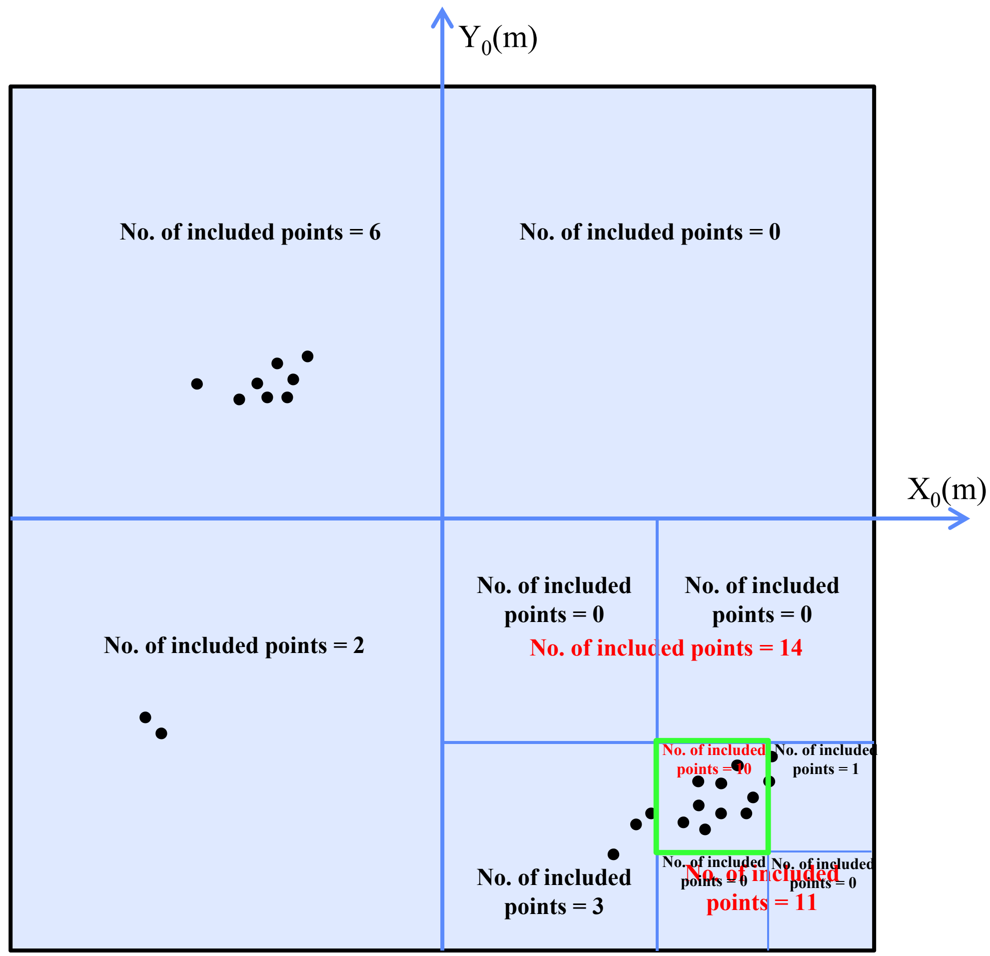


2D representation of brute-force peak detection approach

Note: The radius of the spherical neighborhood changes from one point to the next.

Parameter-Domain Segmentation

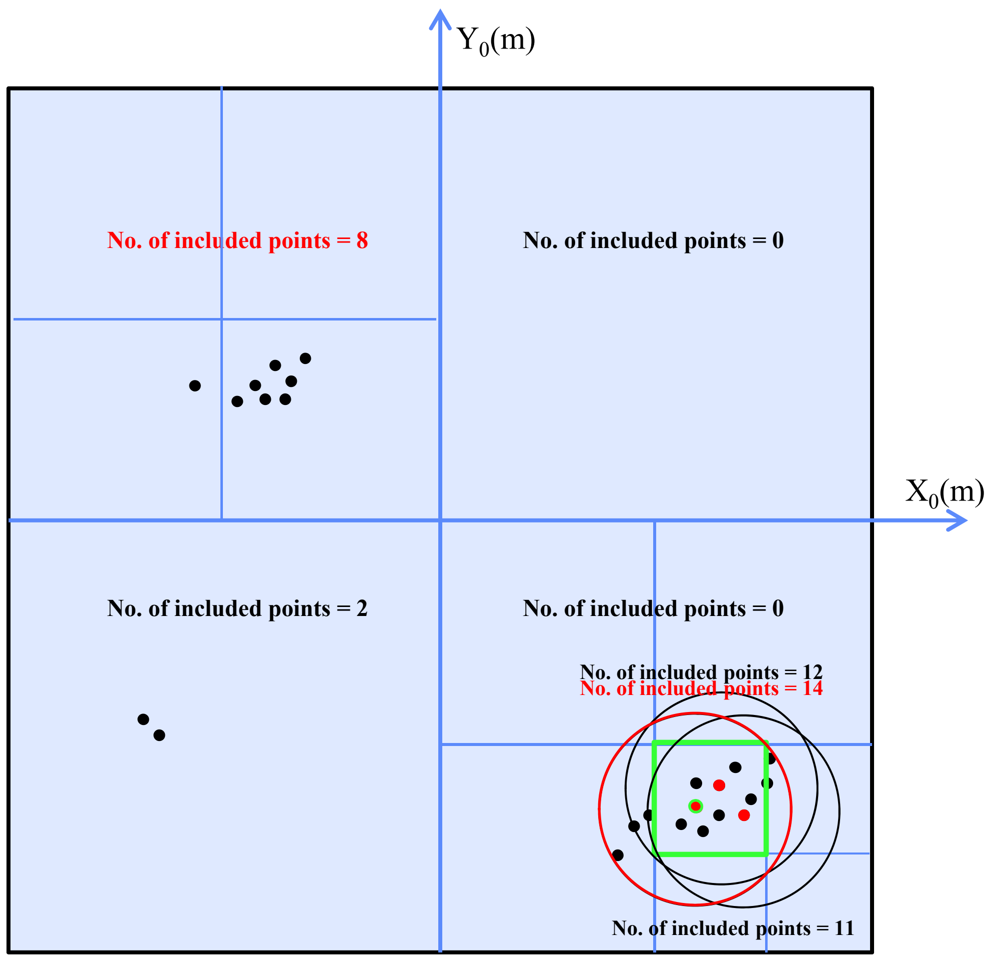
Fast Approach for Peak Detection: Coarse Peak Detection



2D representation of coarse peak detection approach

Parameter-Domain Segmentation

Fast Approach for Peak Detection: Fine Peak Detection



2D representation of fine peak detection approach

Parameter-Domain Segmentation

– **Brute-force Approach:**
  - Advantage: This approach will allow for the detection of the largest peak first, which might avoid over segmentation problems.
  - Drawback: low computational efficiency
– **Fast (Octree-based) Approach:**
  - Advantage: high computational efficiency
  - Drawback: This approach will not guarantee the detection of largest peak first, and this may lead to over segmentation problems.

Parameter-Domain Segmentation

Results from different peak detection methods:

Aerial photo

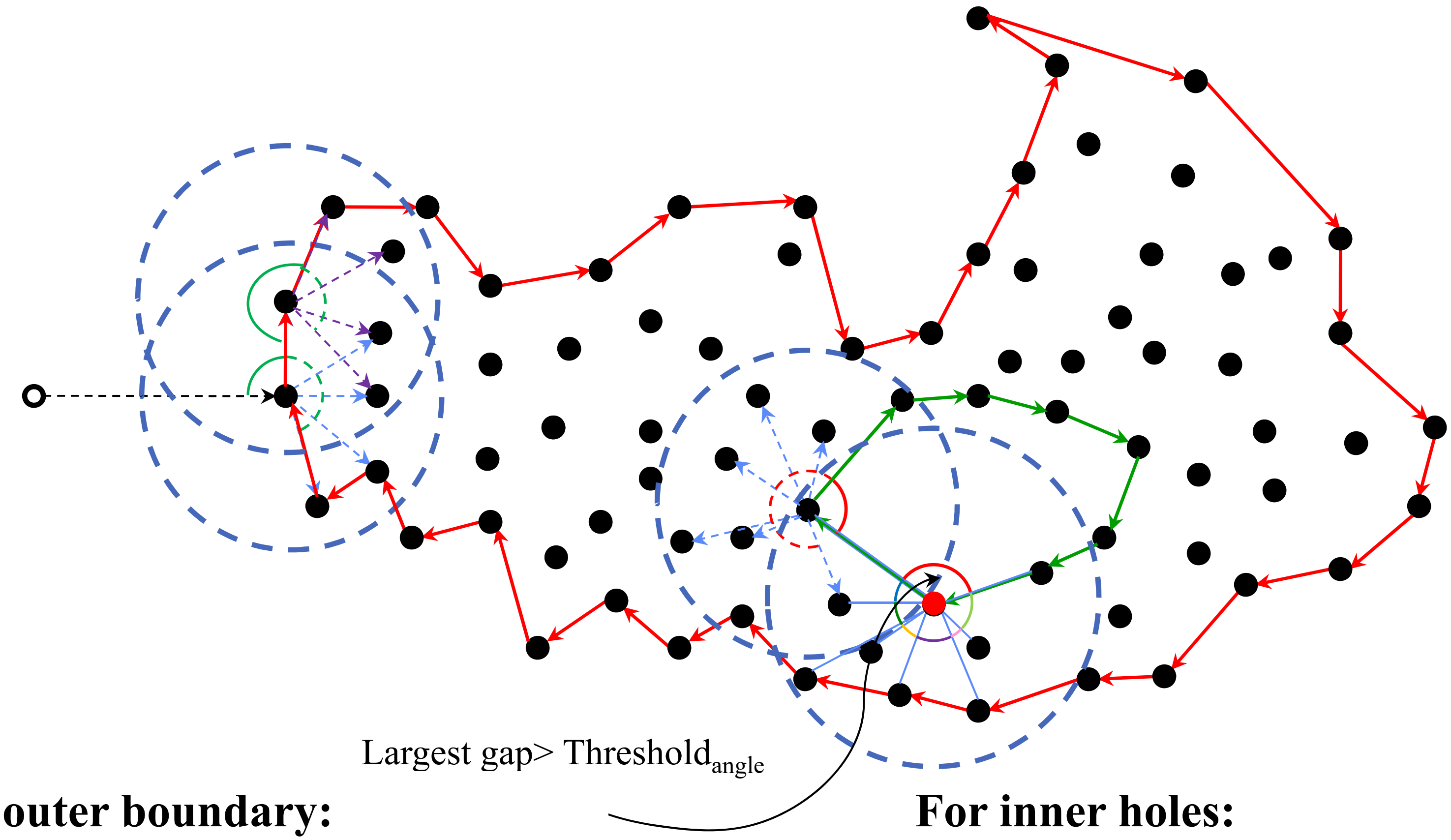
Brute-force clustering approach result

Octree-based clustering approach result

Over-segmentation

Boundary Detection: Hybrid Method

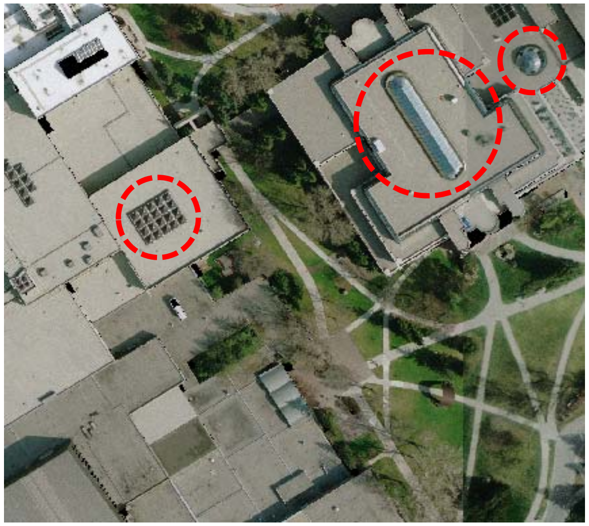
Minimum Convex Hull & Angular Gap Approach



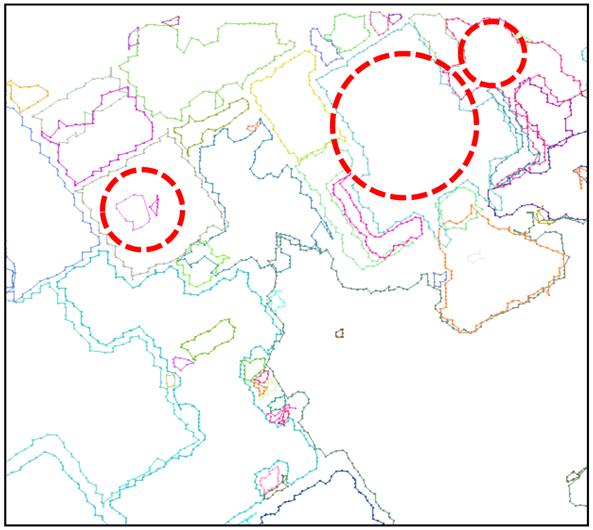
For outer boundary:
Boundary tracing: clock-wise
Angle check: clock-wise

For inner holes:
Boundary tracing: clock-wise
Angle check: counter clock-wise

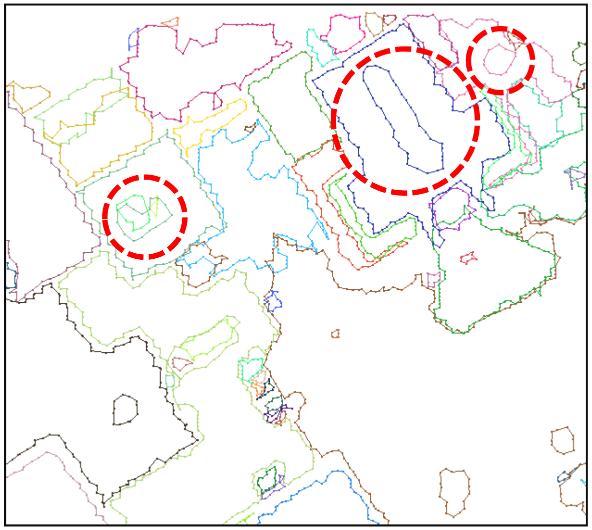
Boundary Detection Results



Orthophoto



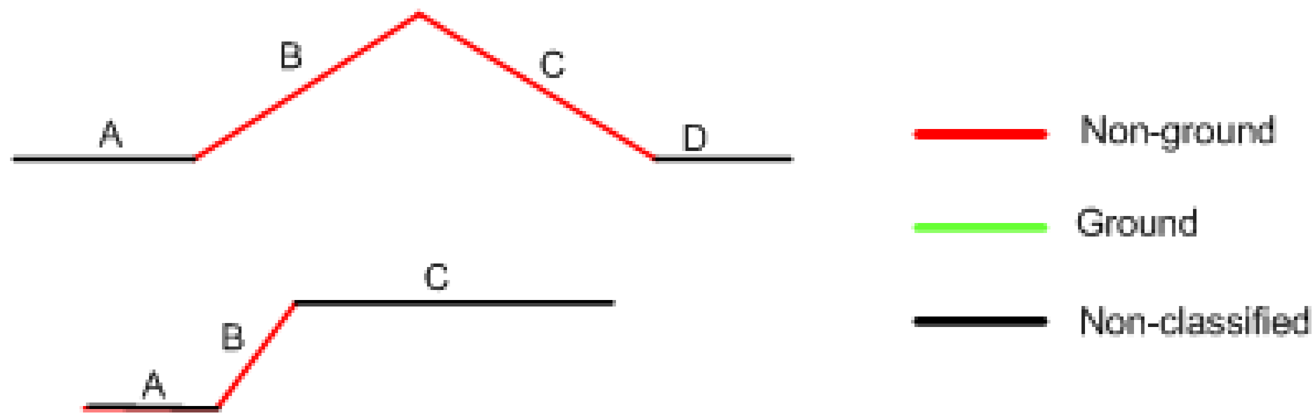
Boundary detection
Minimum convex hull



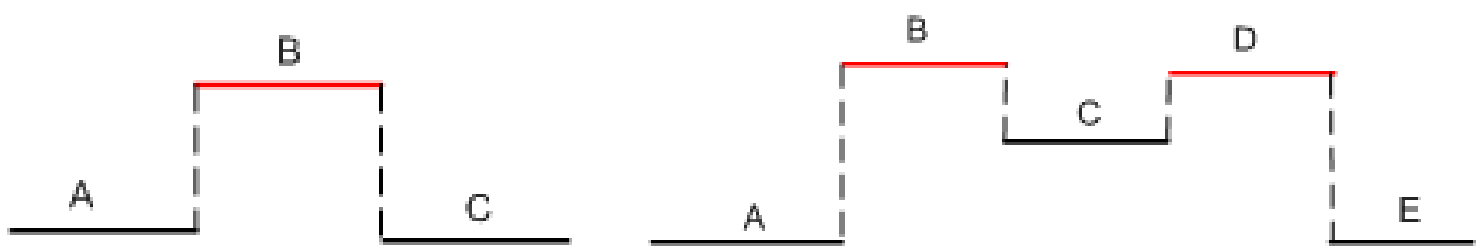
Boundary detection
Hybrid method

The hybrid boundary detection is able to trace the boundaries of holes inside each cluster.

Segmentation-Based Ground/Non-Ground Class.

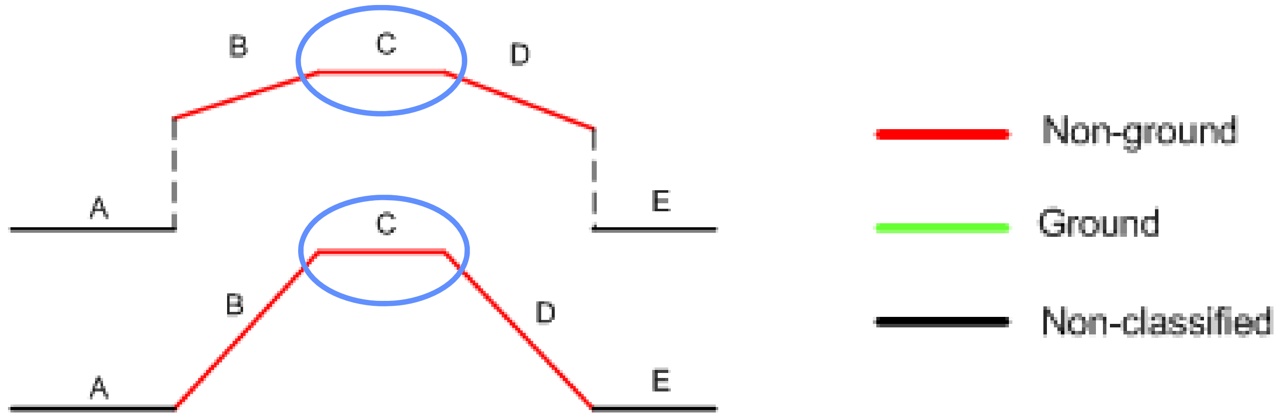


- Segments, whose area is less than a pre-defined threshold, with <u>steep slope</u> are classified as <u>non-ground</u>.

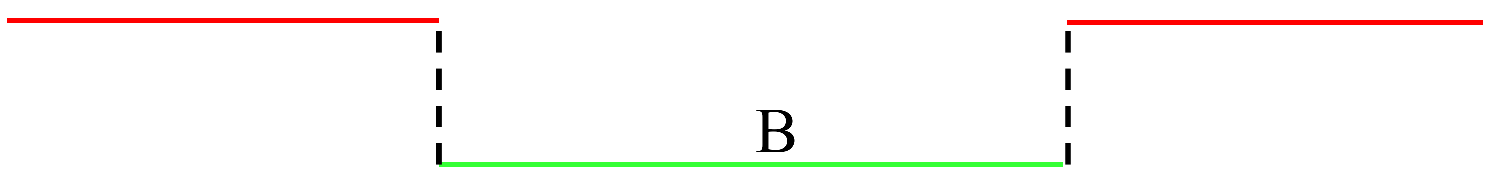


- Starting from the <u>highest segment</u>: segments, which are <u>significantly higher than their 2D neighbours</u>, are classified as <u>non-ground</u> (B & D).

Segmentation-Based Ground/Non-Ground Class.

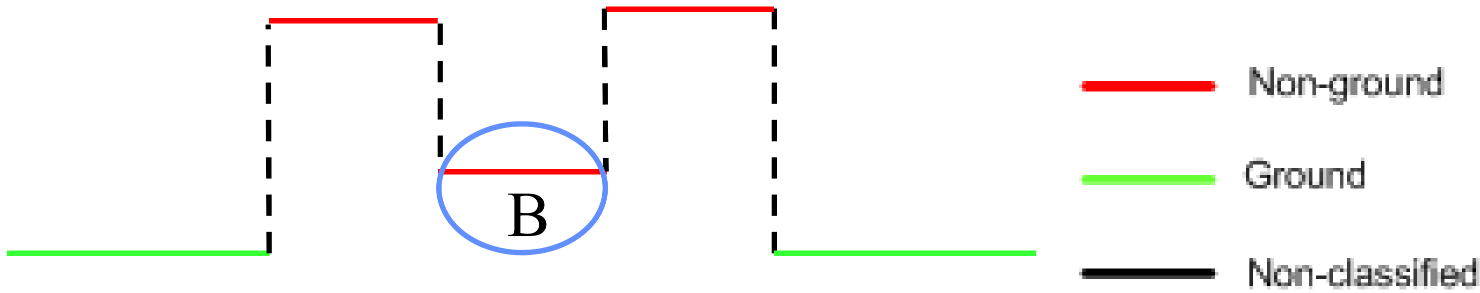


- Segments, which are at the same height or higher than their 2D non-ground neighbours, are classified as non-ground (C) – established through an iterative procedure.

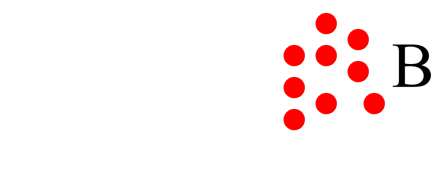


- Starting from the lowest segment: Segments whose area is larger than a pre-defined threshold, are classified as ground (B).

Segmentation-Based Ground/Non-Ground Class.



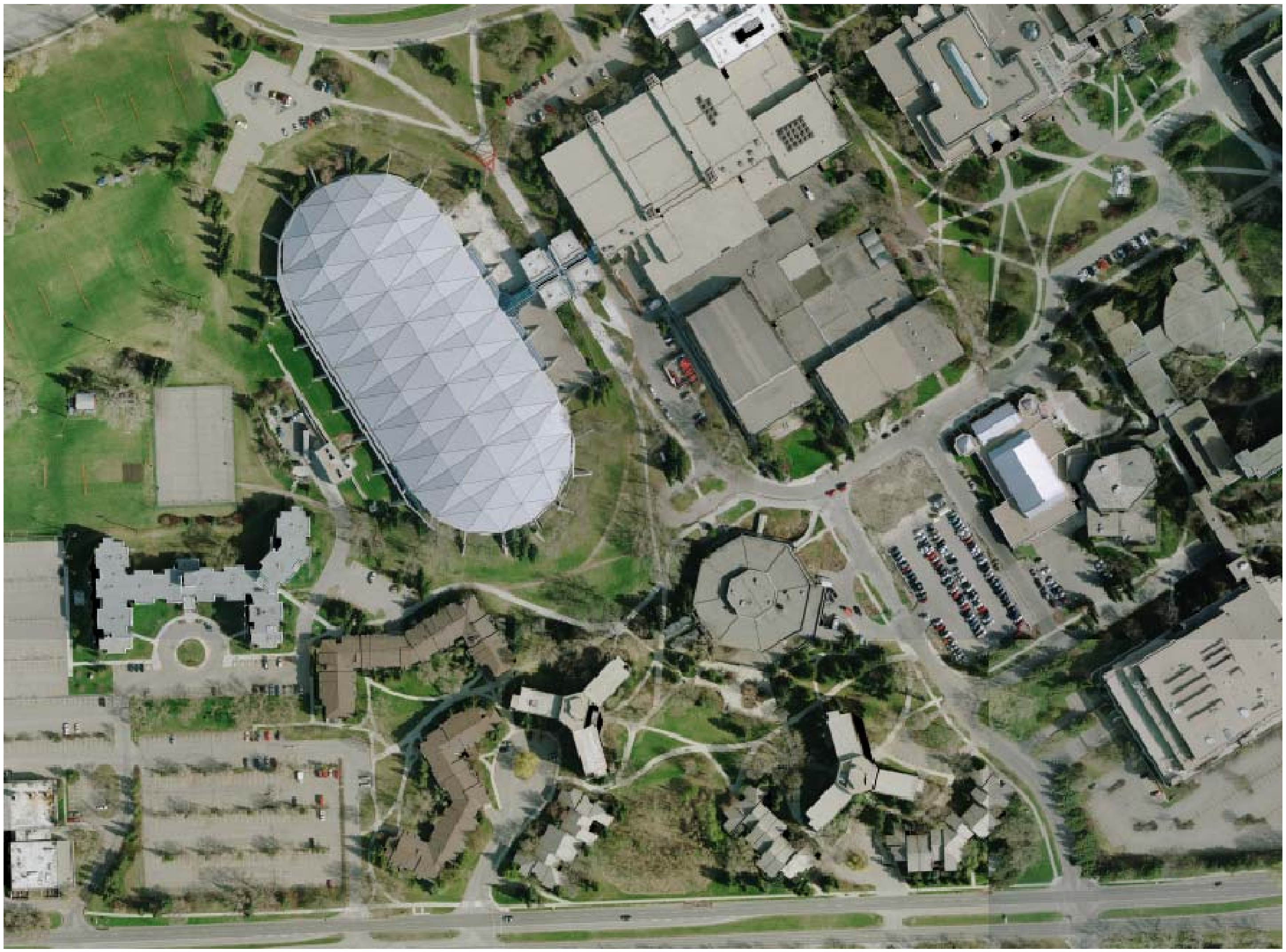
- Starting from the lowest non-classified segment: If the segment is not significantly higher than its 2D nearest ground segment, it will be classified as ground – otherwise, it will be non-ground (B).



- For rough groups, if the majority of the points in the group are significantly higher than the 2D nearest ground segment, the group will be classified as non-ground (B).

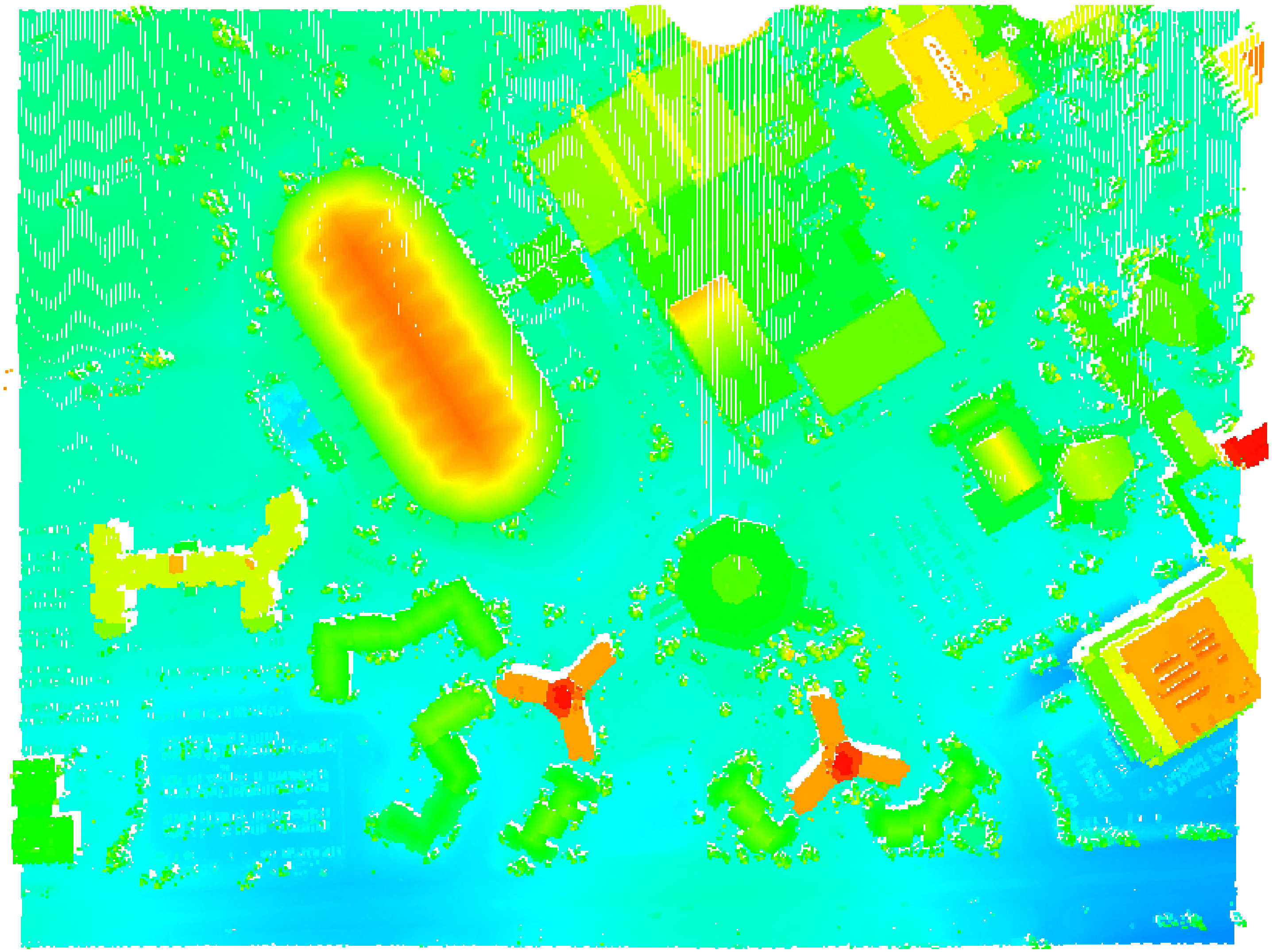
LiDAR Data Classification and Segmentation

- Orthophoto over the test area



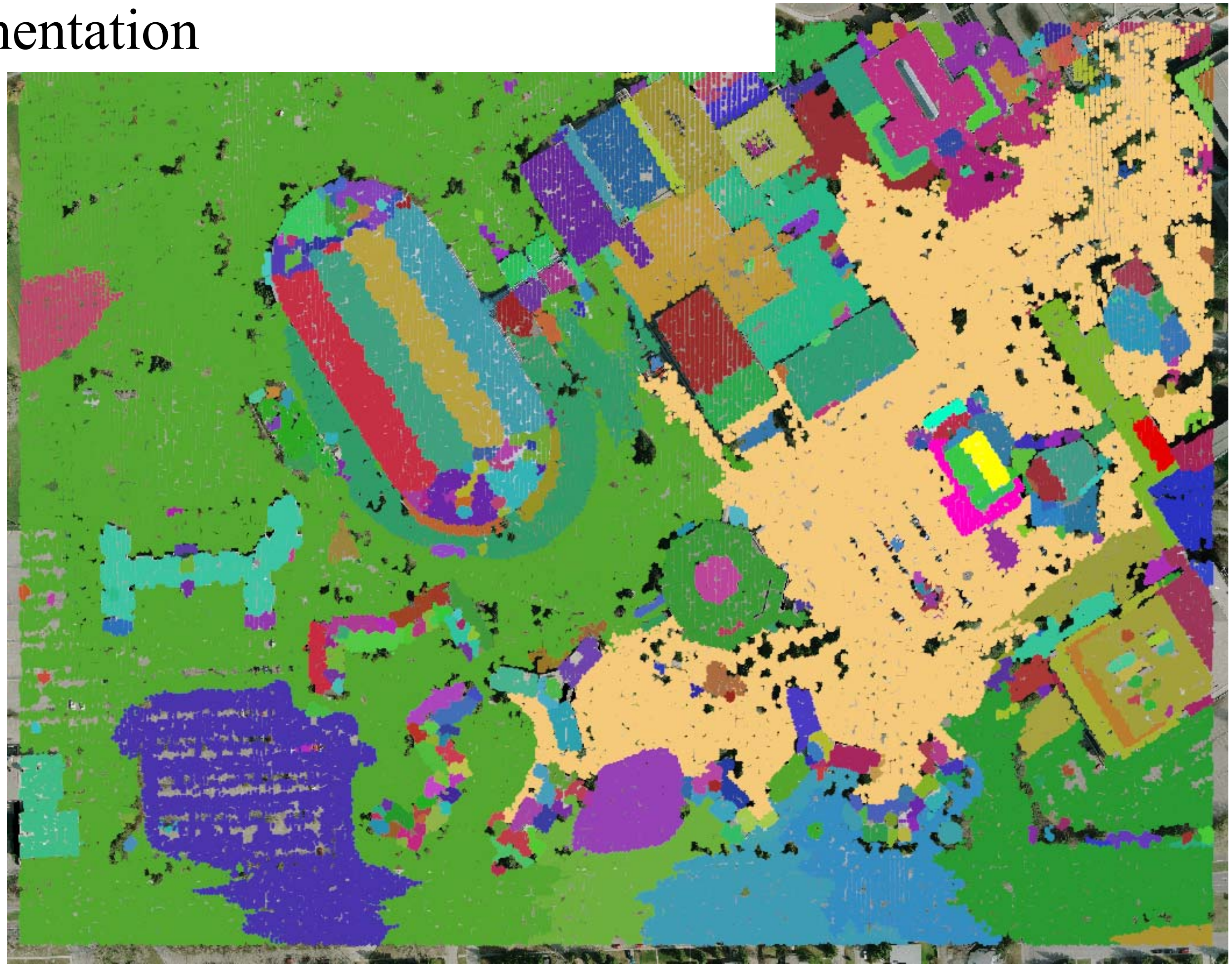
LiDAR Data Classification and Segmentation

- Original LiDAR data



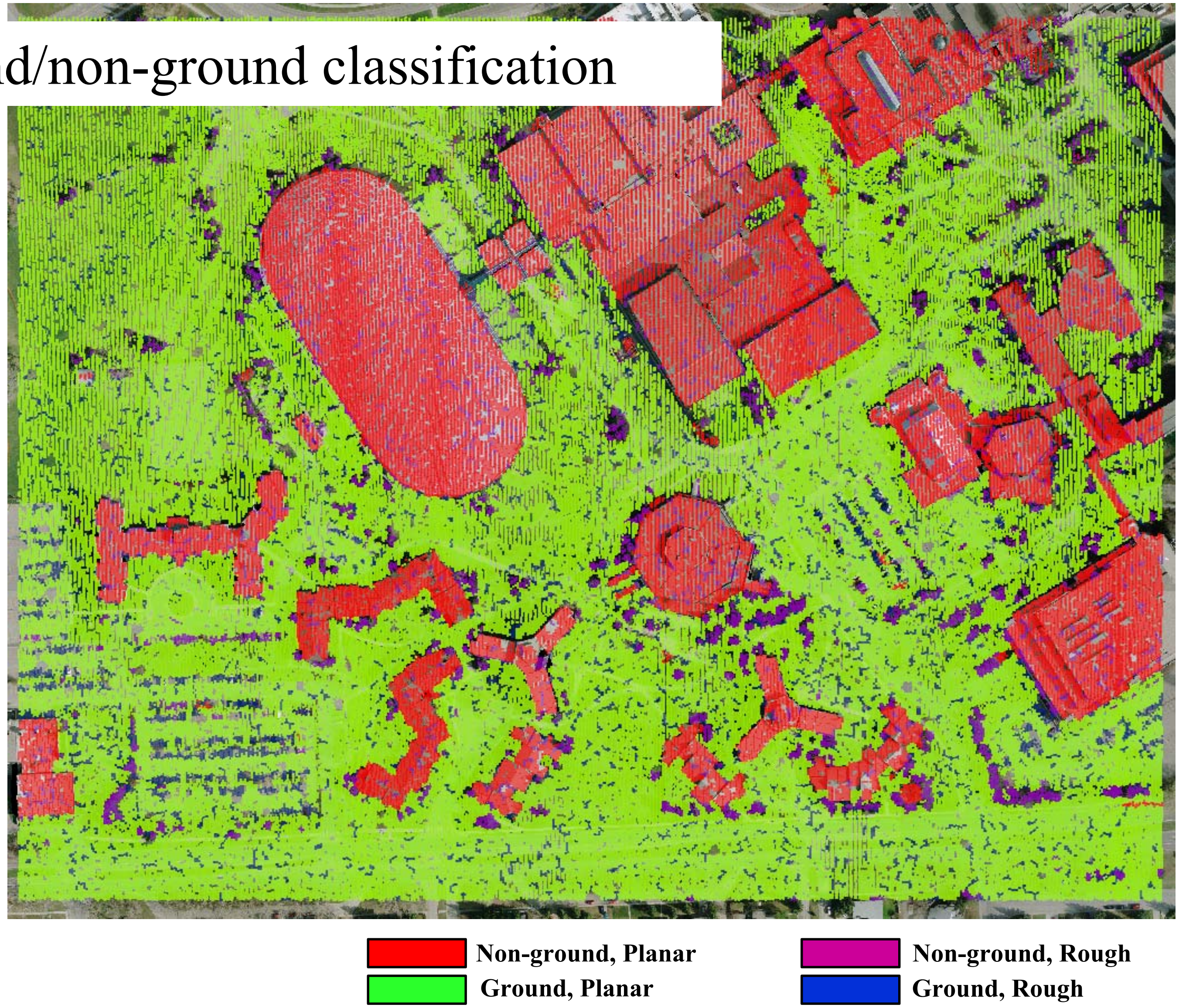
LiDAR Data Classification and Segmentation

- Segmentation



LiDAR Data Classification and Segmentation

- Ground/non-ground classification

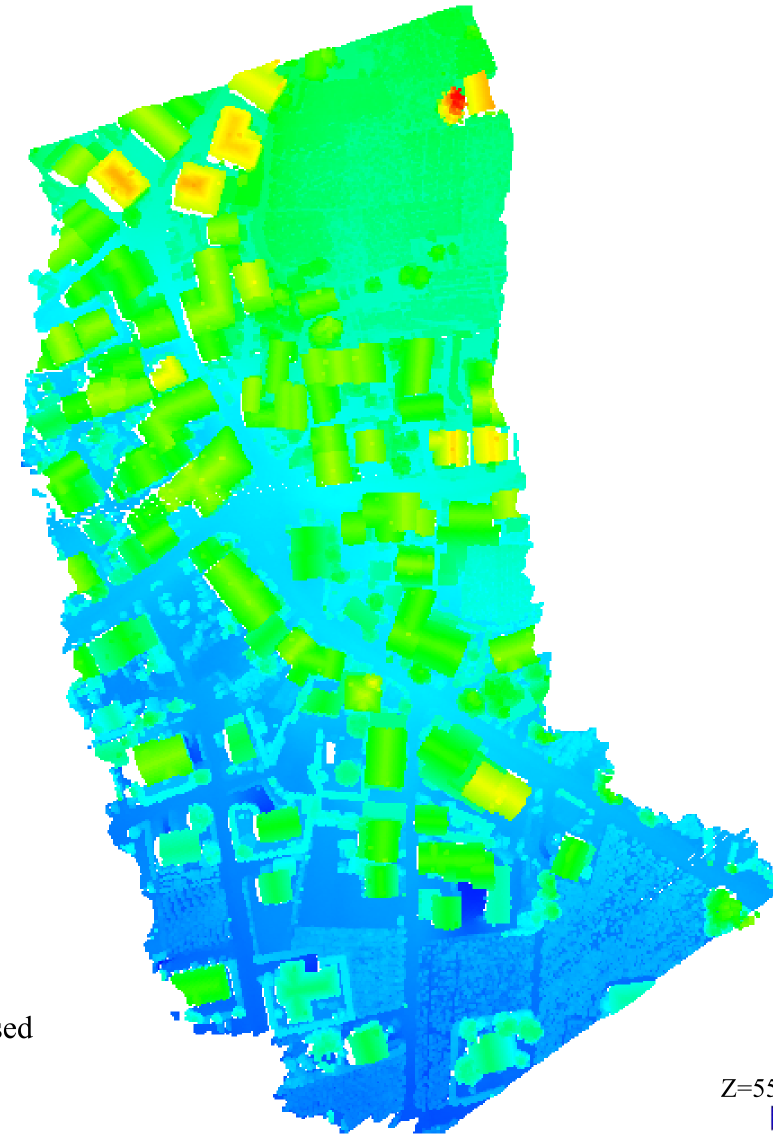


Experimental Results: Example 1

- Location: Switzerland
- Mission: Airborne
- Mean point density: 6 Pnts/m^2

Threshold	Value
No. Of neighbouring points for LPD calculation	25
No. Of neighbouring points for best fit plane definition	18
Height of cylinder	0.8 m
Percentage of plane	95%
$\Delta\alpha$	10°
Δd	1m
Size of minimum detectable cluster	8 points

Original Data



Z=557.7m Z=581.1m

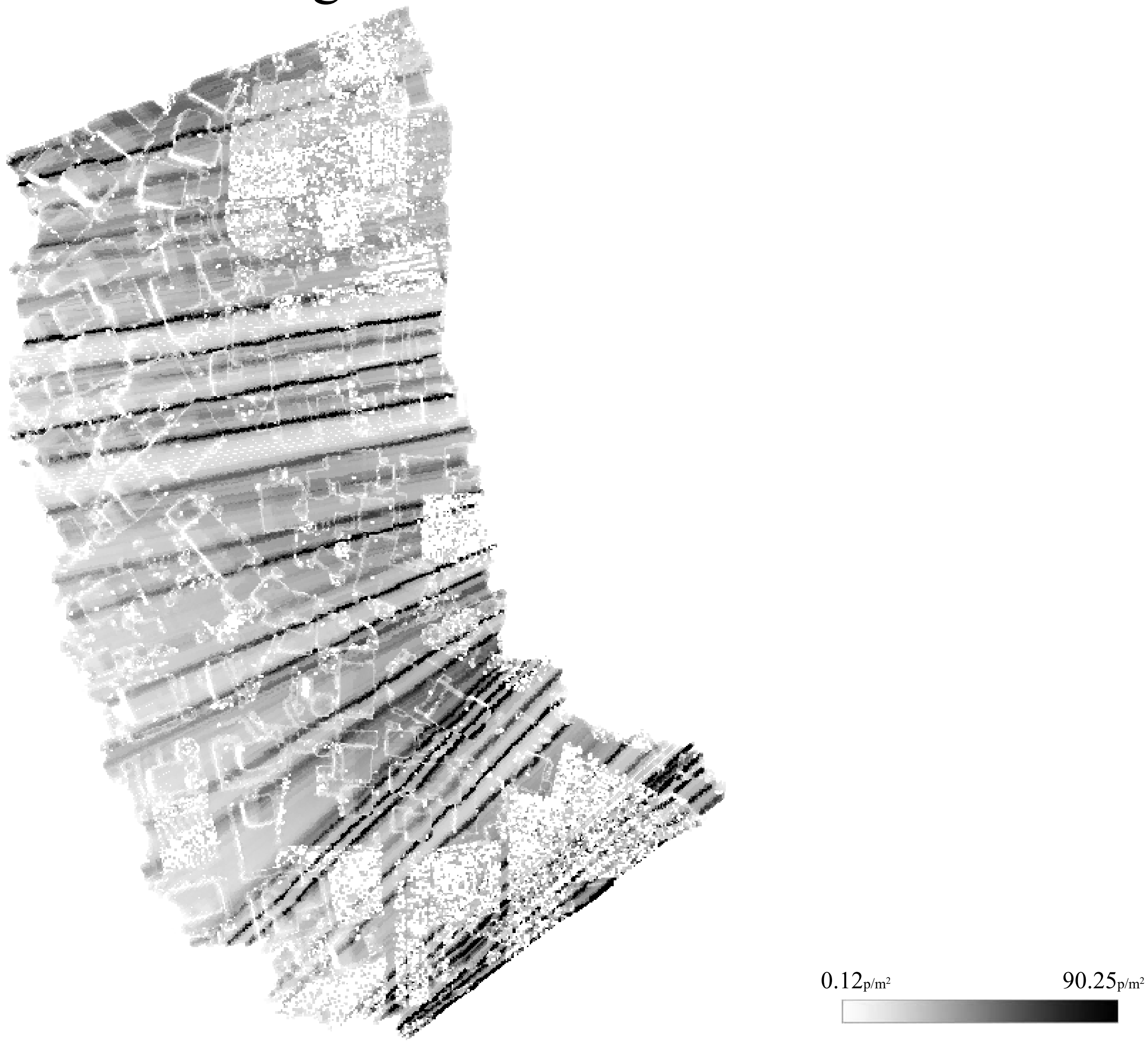
The color of each point is determined based on its height.

Point Density Map

Approximate Method

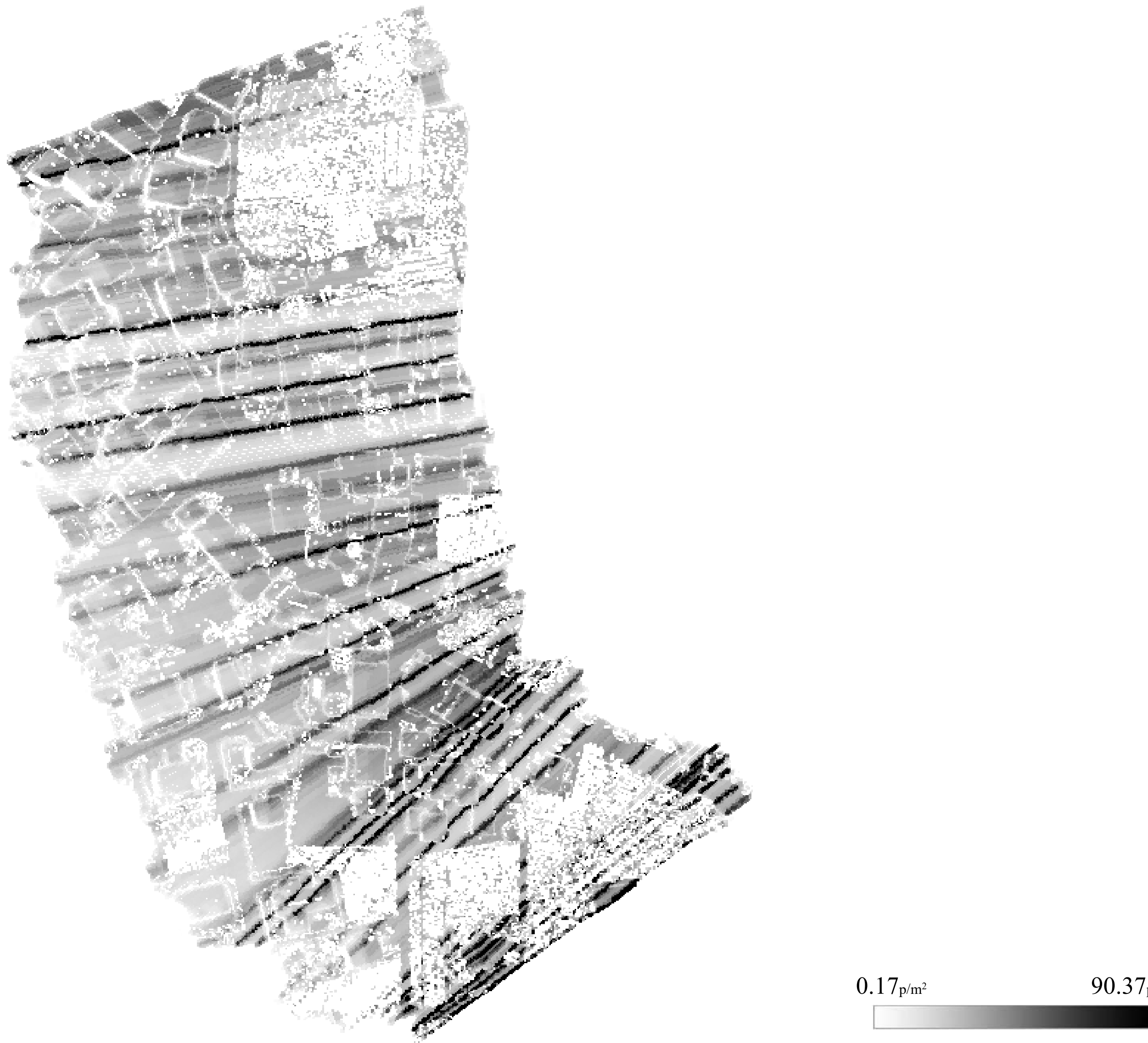
Point Density Map

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



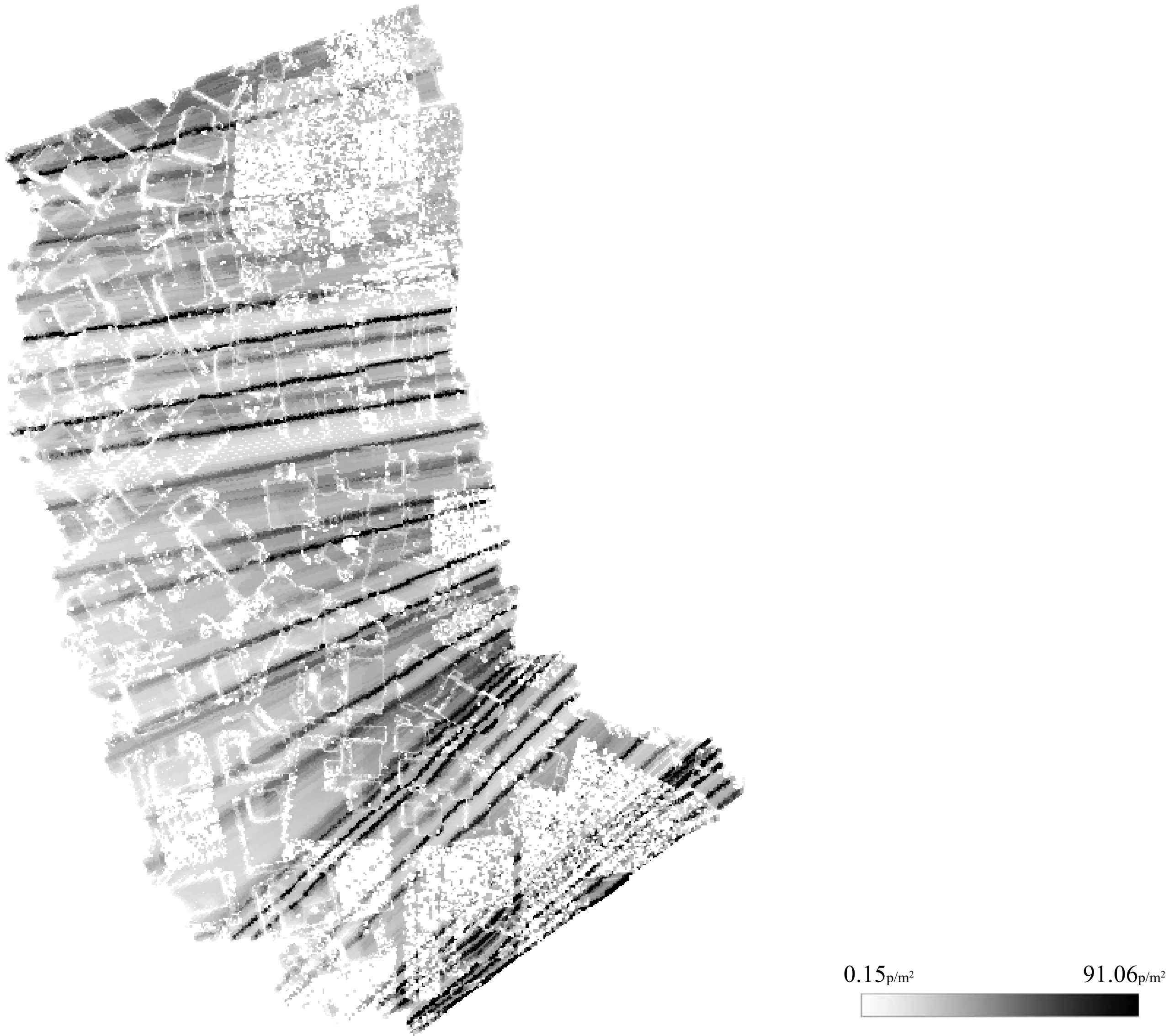
Point Density Map

Dispersion of the point's 3D neighbours relative to the POI



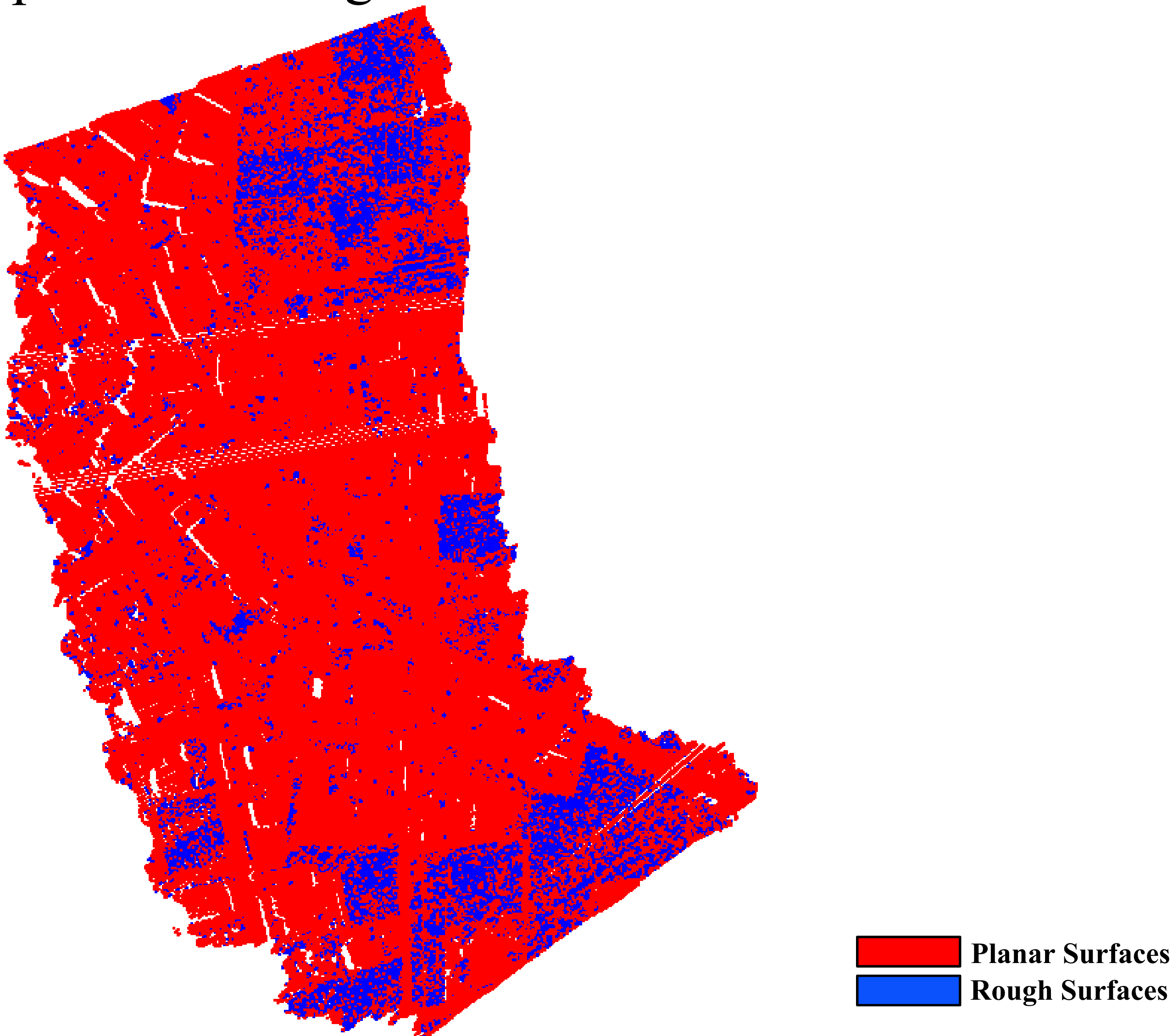
Point Density Map

Adaptive Cylinder



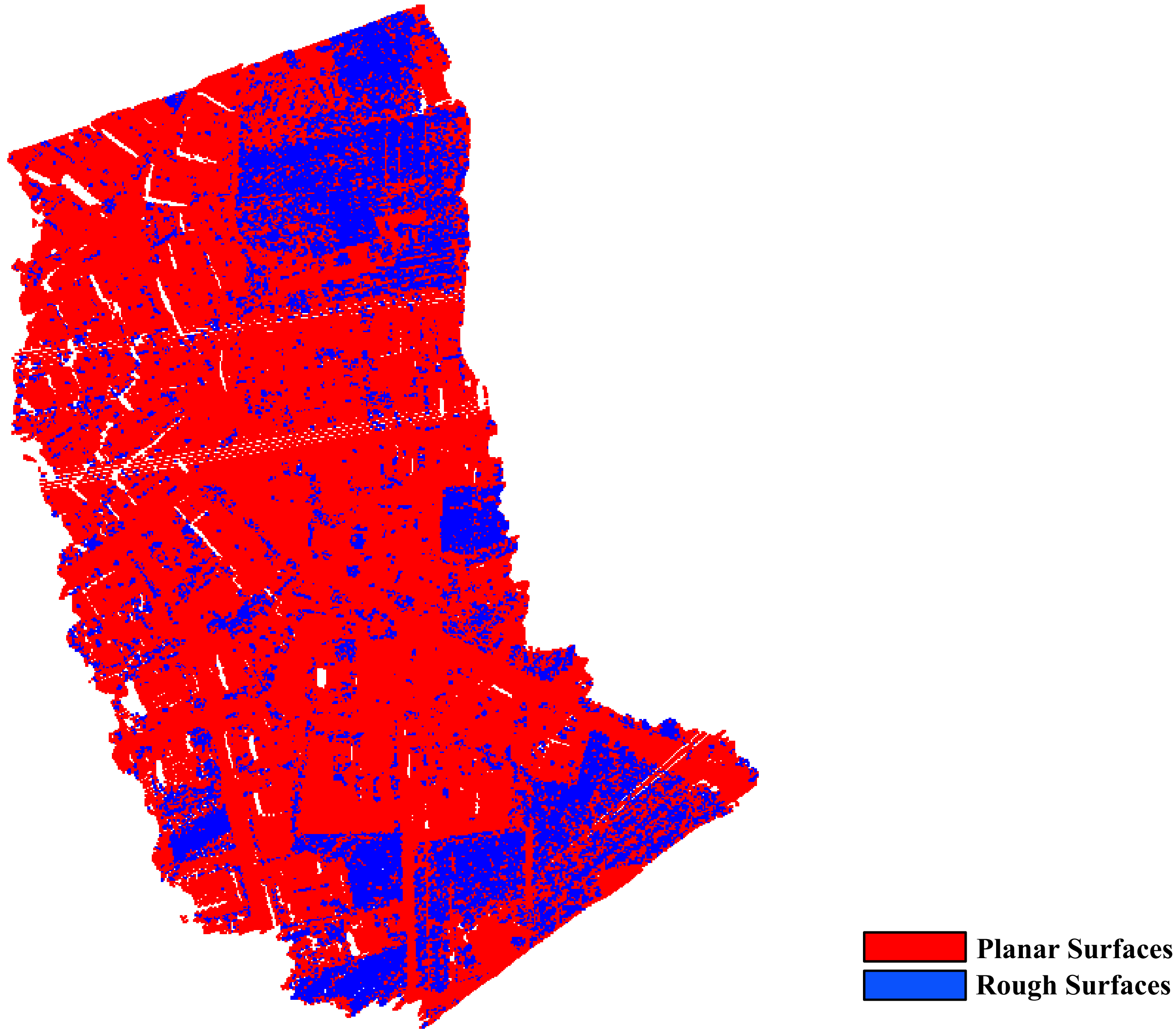
Rough and Planar Points Classification

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



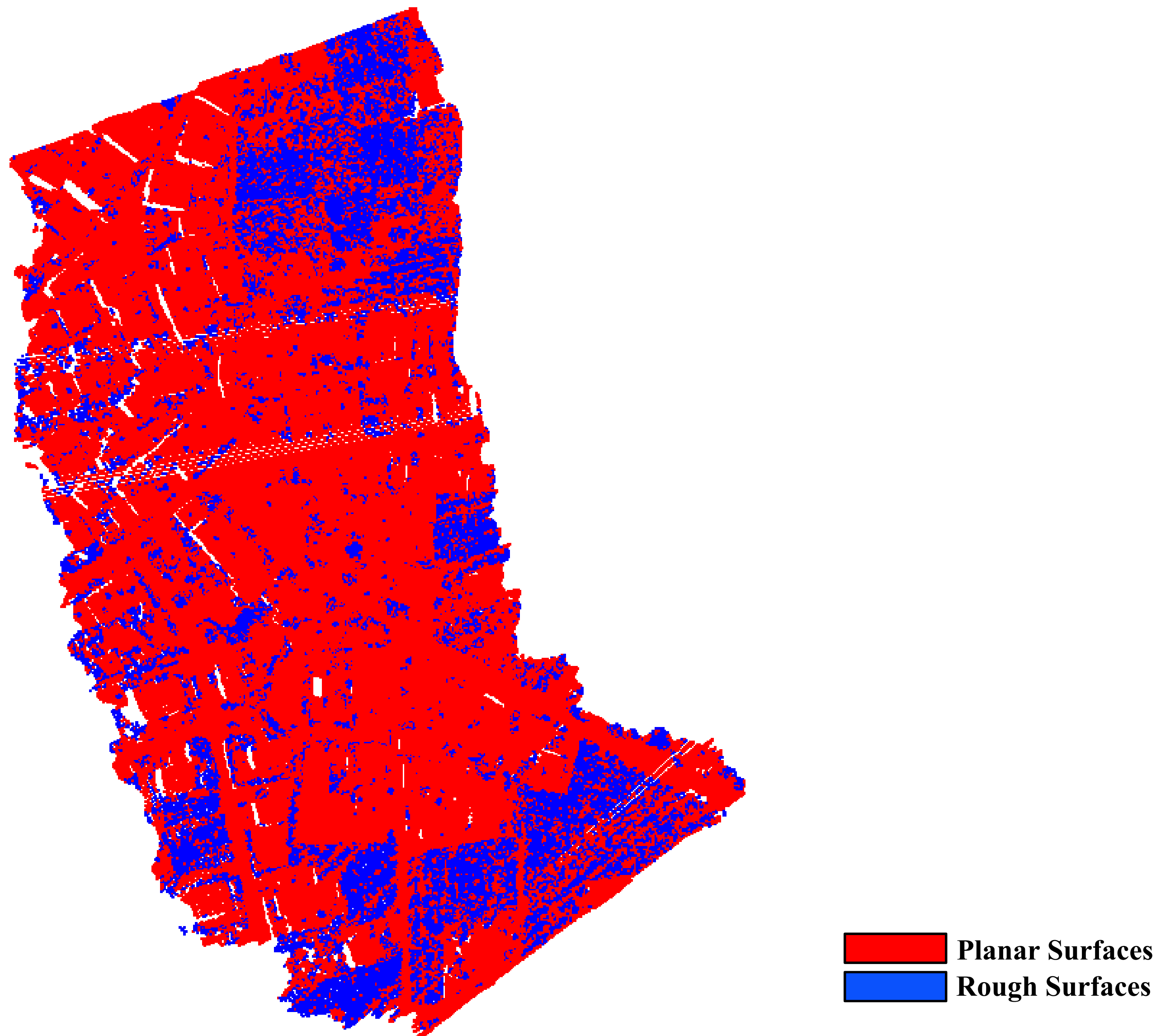
Rough and Planar Points Classification

Dispersion of the point's 3D neighbours relative to the POI

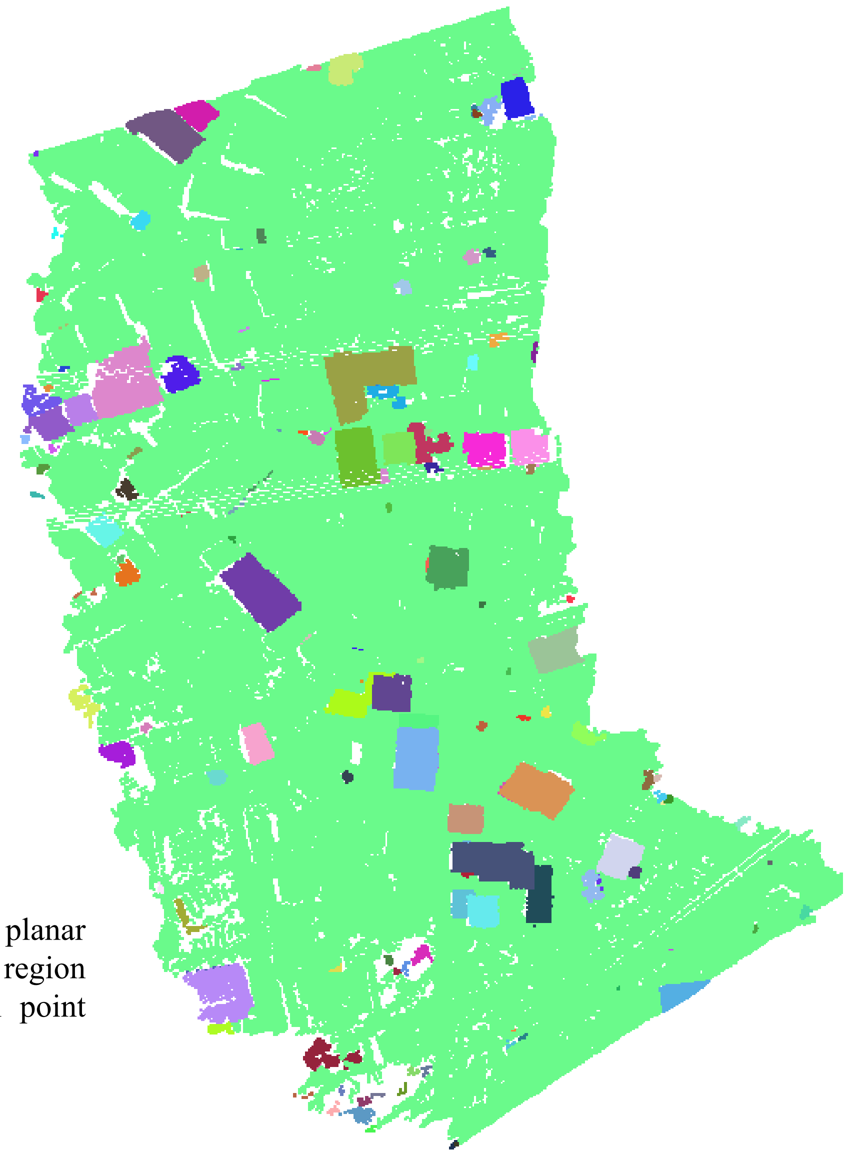


Rough and Planar Points Classification

Adaptive Cylinder



Grouping



Each color represents a group of planar points which is derived using a region growing algorithm based on local point density variations

Segmentation Result (Brute-force Clustering)

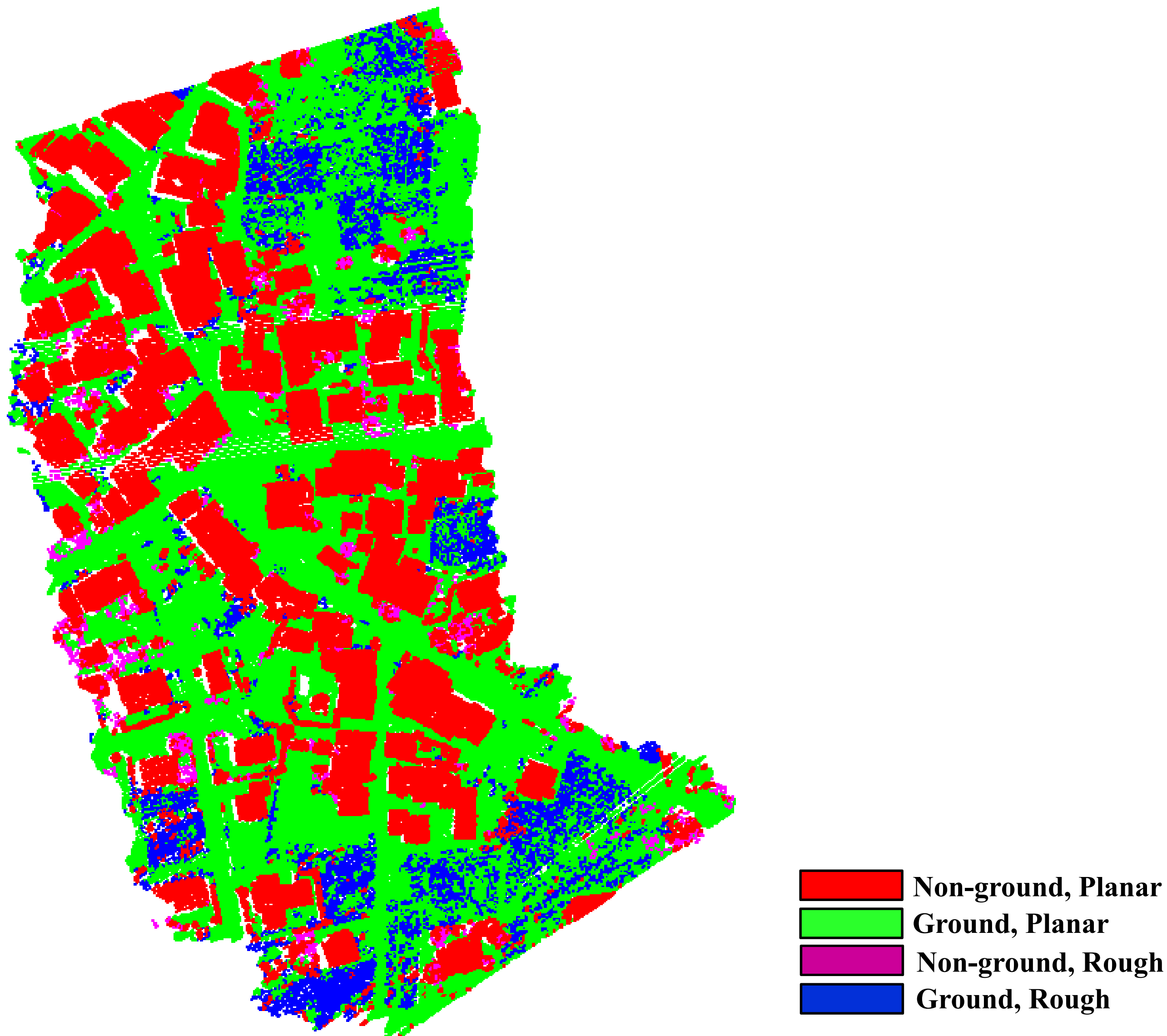
Each color represents a planar cluste
which is derived using a developed se
approach.

Segmentation Result (OcTree Search)

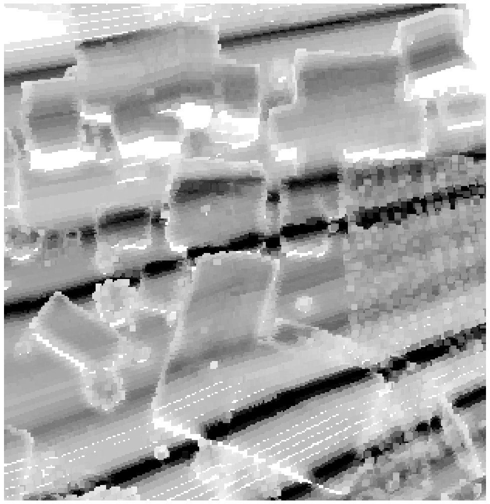
Each color represents a planar cluster of points which is derived using a developed segmentation approach.

Boundary Detection: Hybrid Approach

Ground and Non-Ground Classification

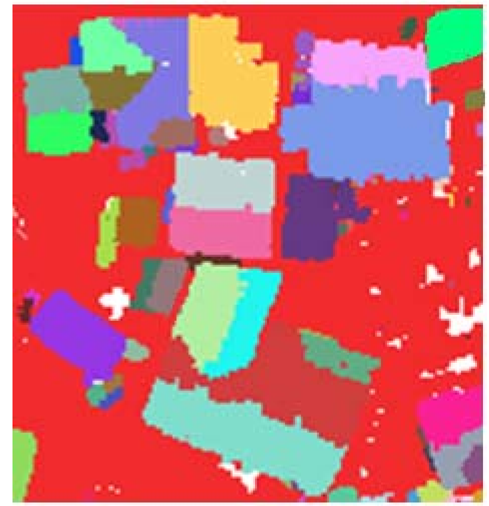


Detailed View (Brute-force Clustering)

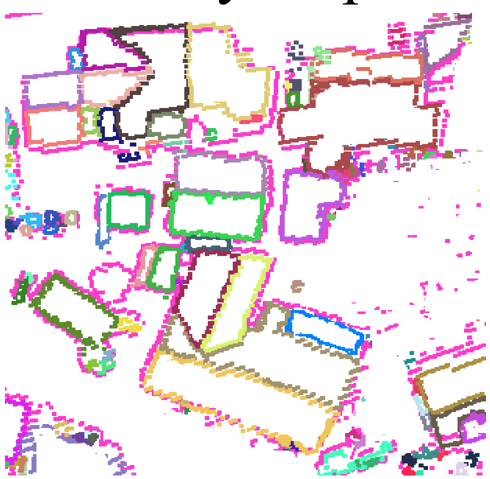


Point density map

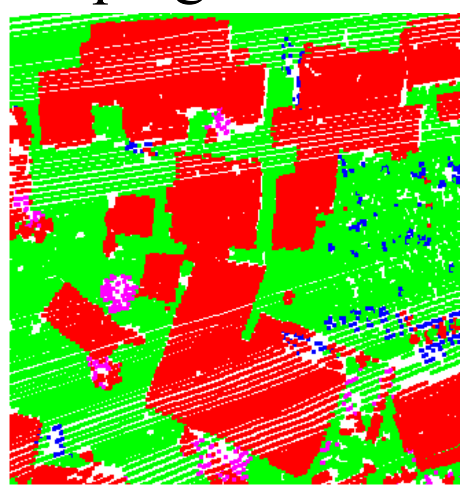
Grouping



Segmentation
(brute-force method)

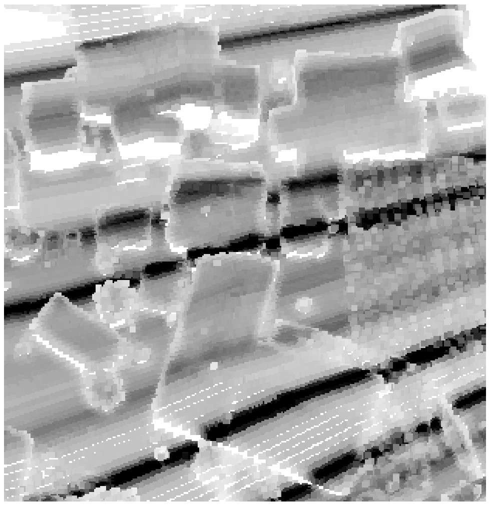


Boundary detection

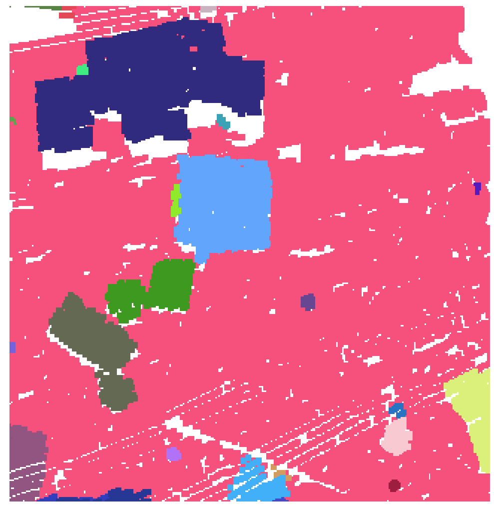


G and NG classification

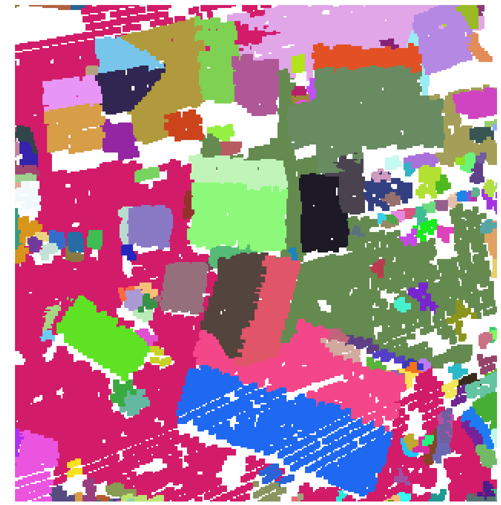
Detailed View (OcTree Search)



Point density map

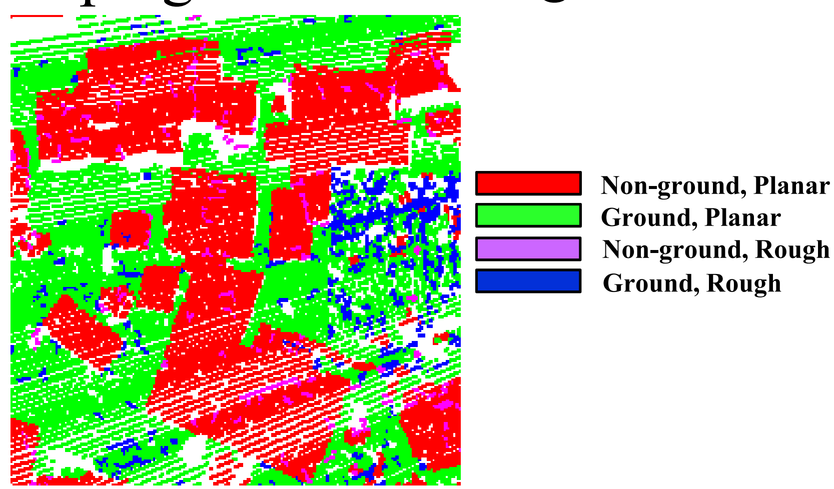


Grouping



Segmentation

Boundary detection



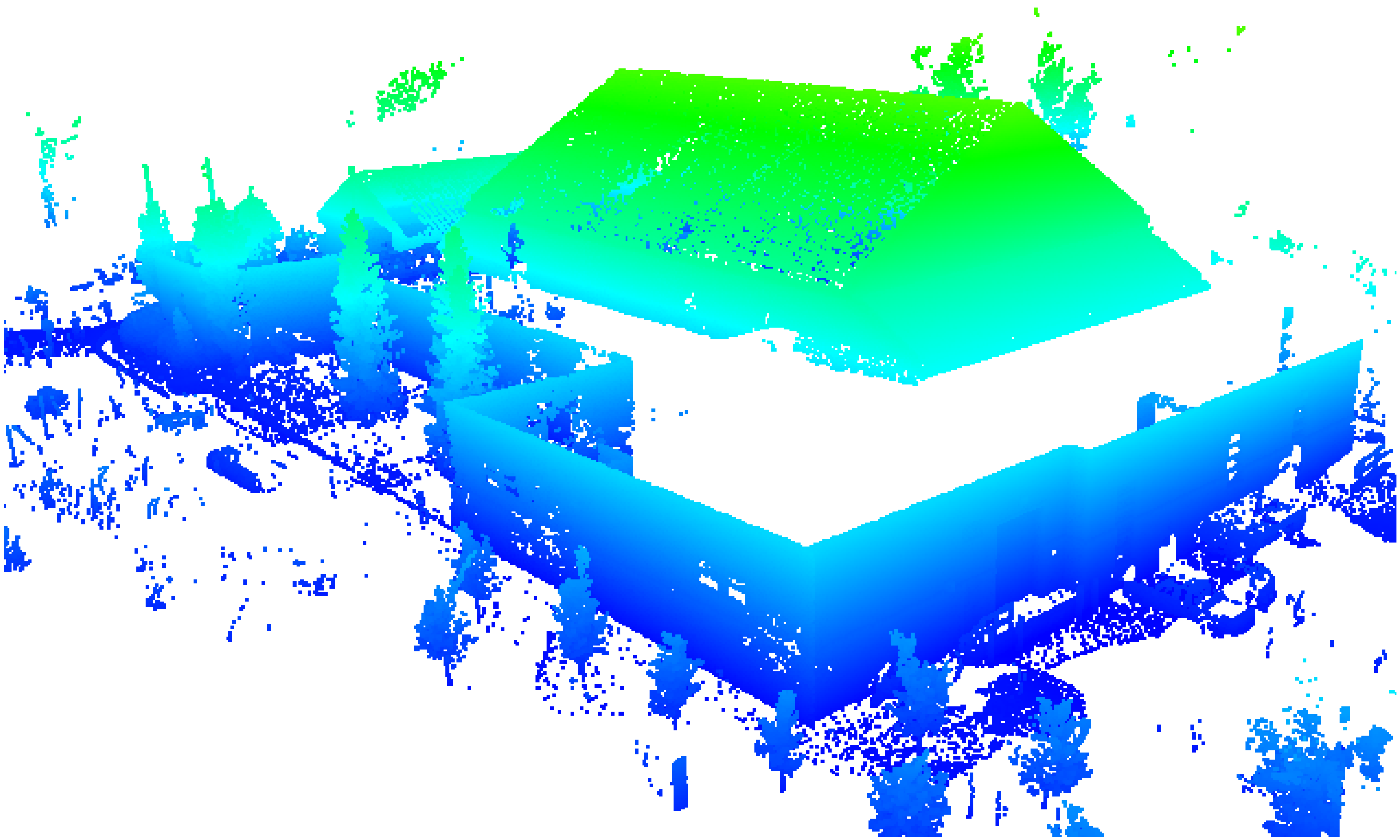
G and NG classification

Experimental Results: Example 2

- Location: Rozsa Center, University of Calgary
- Mission: Terrestrial
- Mean point density: 10608 Pnts/m^2

Threshold	Value
No. Of neighbouring points for LPD calculation	50
No. Of neighbouring points for best fit plane definition	18
Height of cylinder	0.04 m
Percentage of plane	85%
$\Delta\alpha$	20°
Δd	0.2 m
Size of minimum detectable cluster	25 points

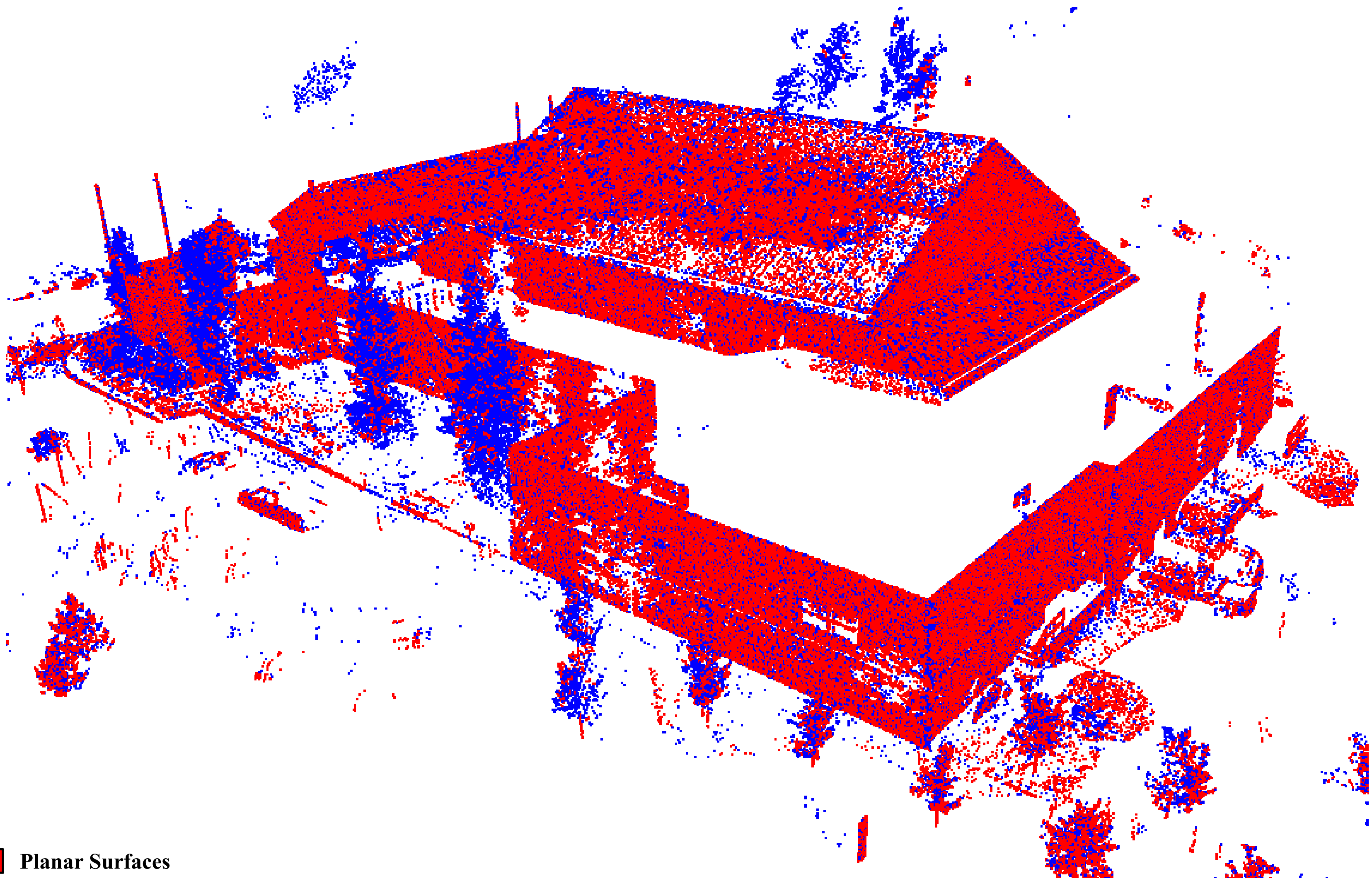
Original Point Cloud



The color of each point is determined based on its height.

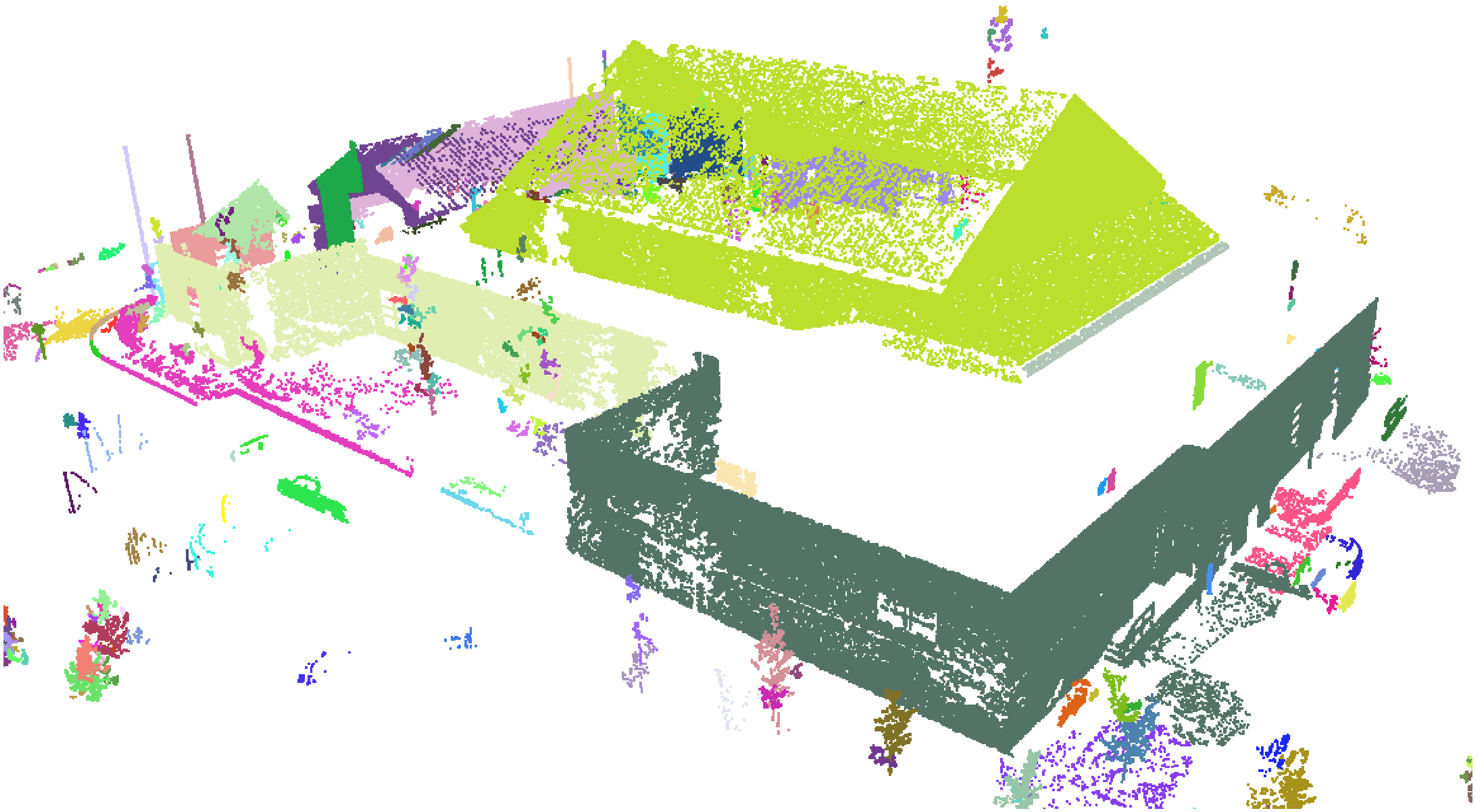
Point Density Map

Rough and Planar Points Classification



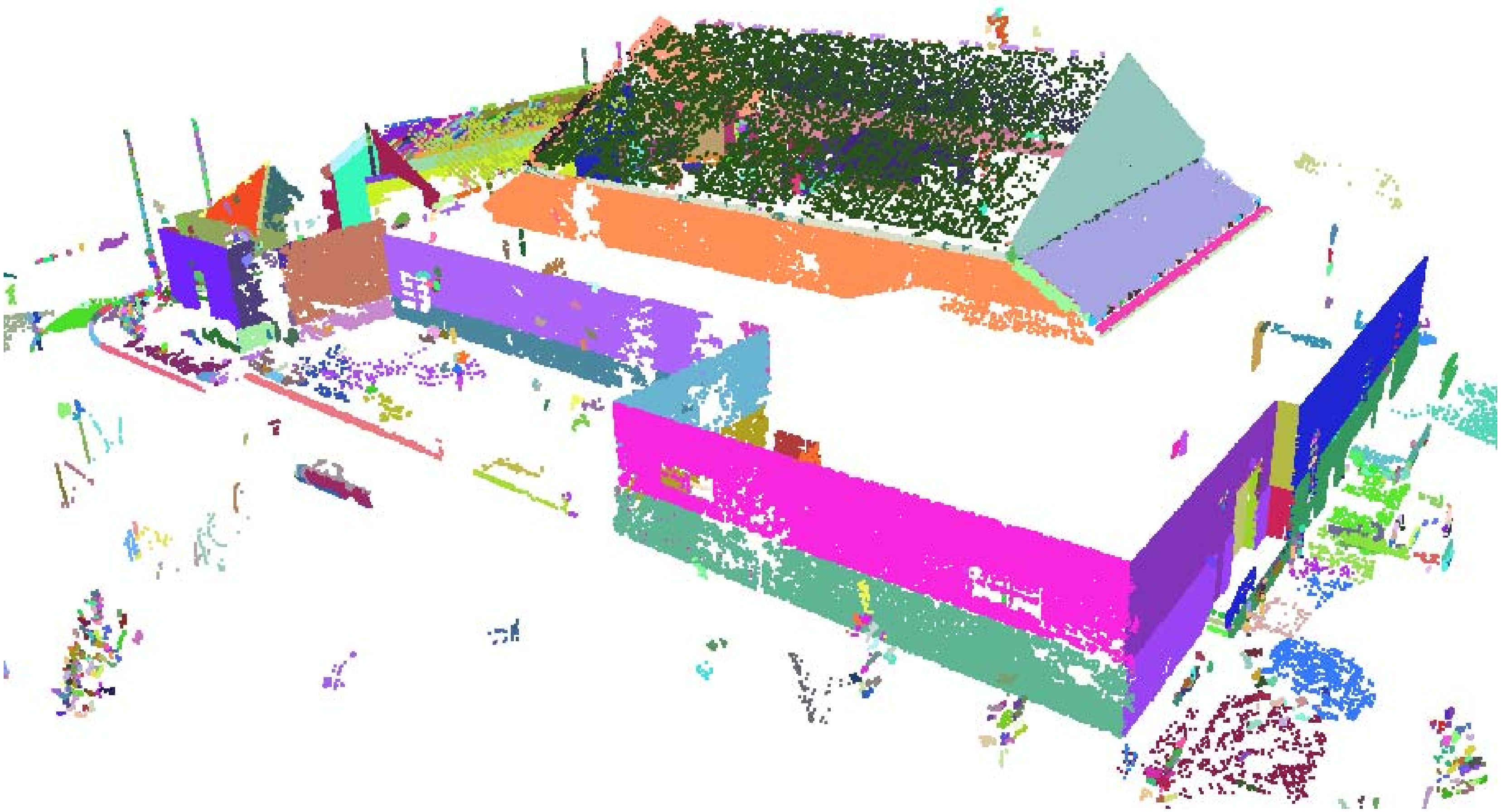
Planar Surfaces
Rough Surfaces

Grouping

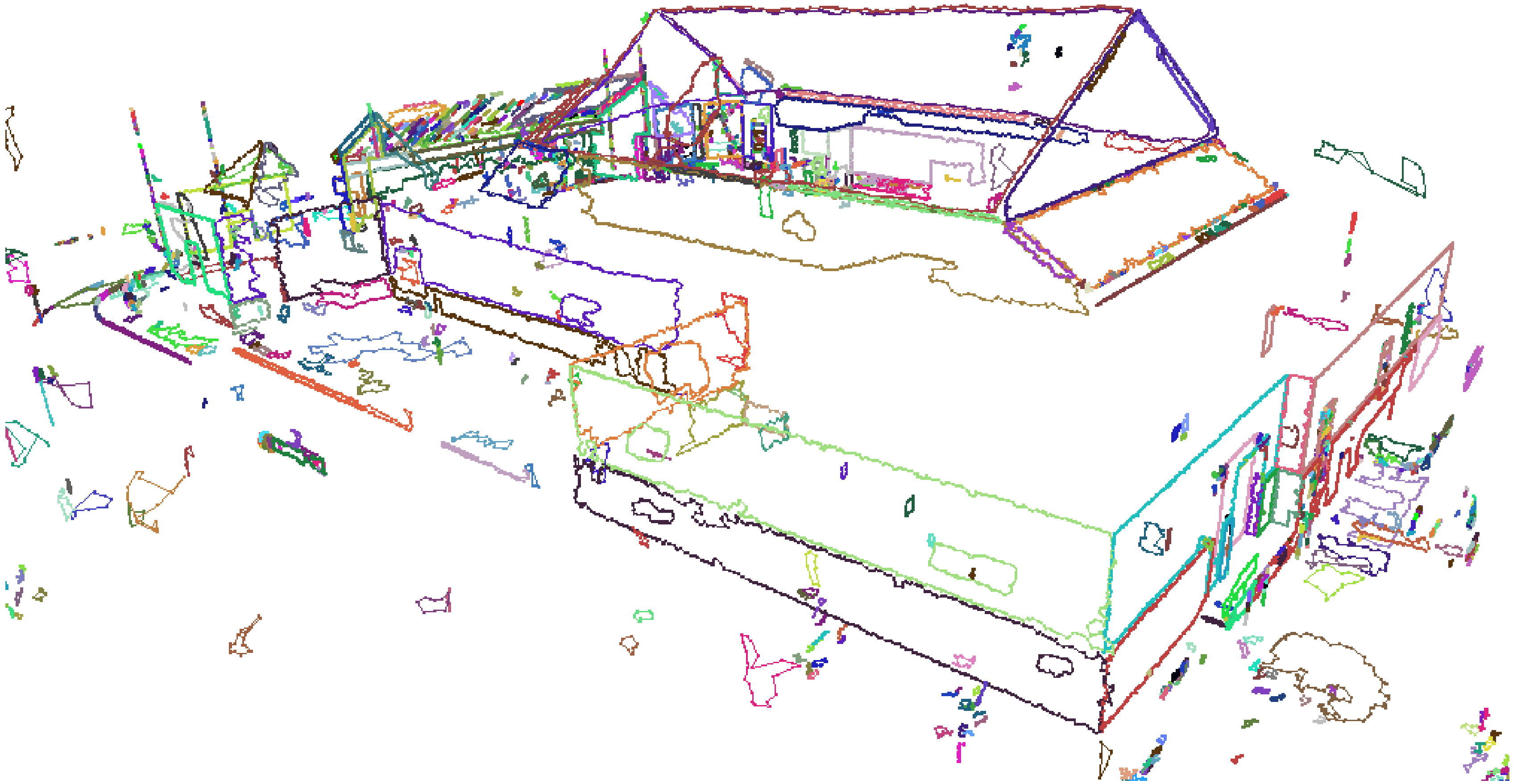


Each color represents a group of planar points which is derived using a region growing algorithm based on local point density variations.

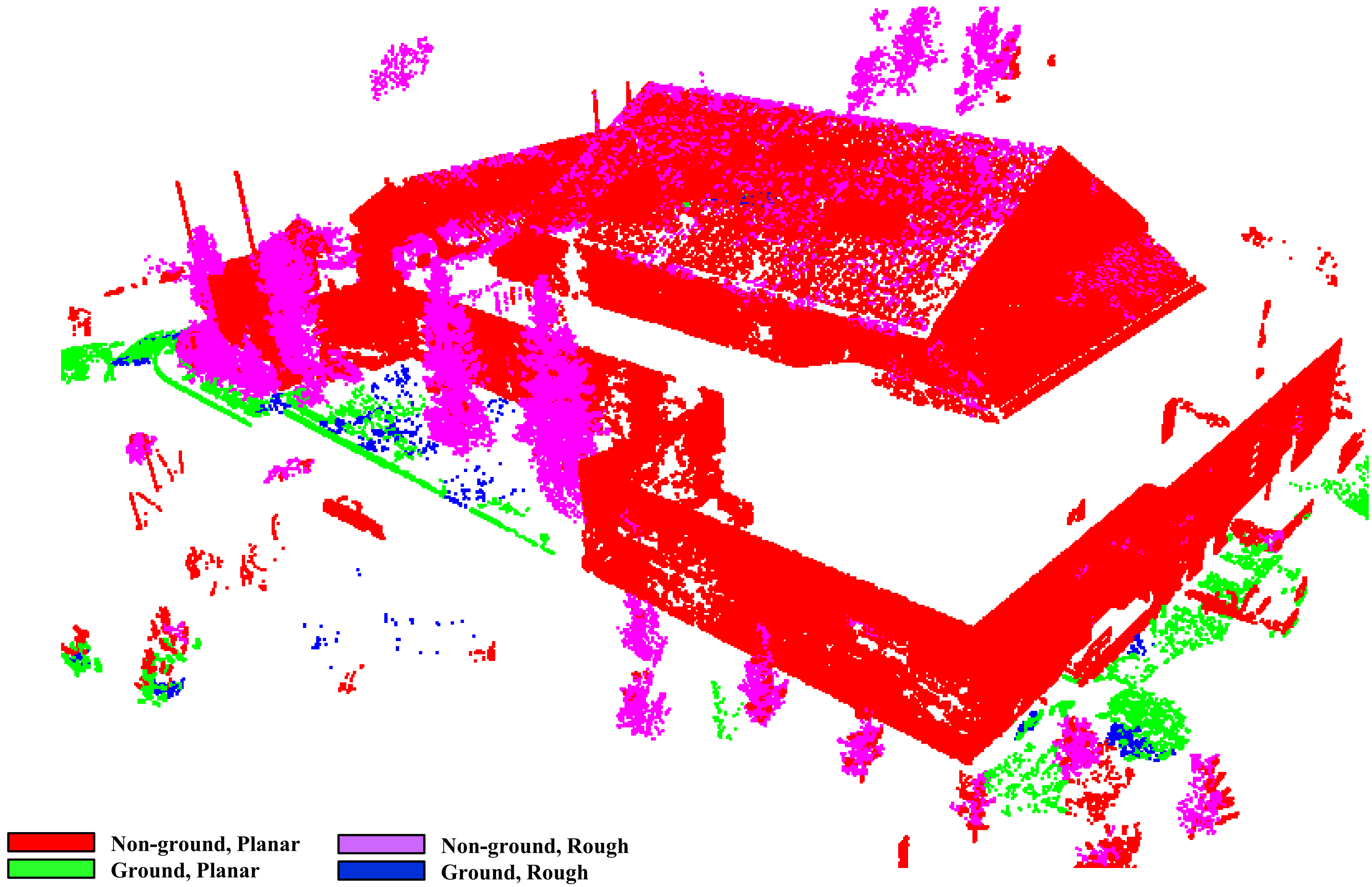
Segmentation Results



Boundary Detection: Hybrid Method



Ground and Non-Ground Classification



Conclusions

- The proposed segmentation technique is capable of handling point cloud data with varying point density, surface slope, and orientation.
- Different measures have been introduced to derive meaningful Local Point Densities (LPD) for the individual points in datasets, which are captured by airborne of terrestrial systems.
- Computed attributes for the segmentation procedure take into consideration: a) local point density, b) surface trend , and c) noise level in the data.
- The peak detection in the attribute space does not employ a tessellation scheme, which is commonly used for parameter-domain segmentation.
- Two different peak detection techniques have been introduced with varying level of computational efficiency.

Conclusions

- The extent of detected clusters is adaptively changed depending on the attributes of such cluster, which makes the segmentation outcome independent of the origin location.
- The segmentation approach considers both similarity of attributes as well as the proximity of the points associated with these attributes.
- The proposed method for boundary detection is able to detect the boundary of holes inside a cluster.
- QC procedures for evaluating the segmentation outcome have been developed.
- The segmentation-based classification approach overcomes the defects of point-based classification methods while considering the nature of the objects the laser points belong to.

Quality Control of LiDAR Data Segmentation

Planar Feature Segmentation

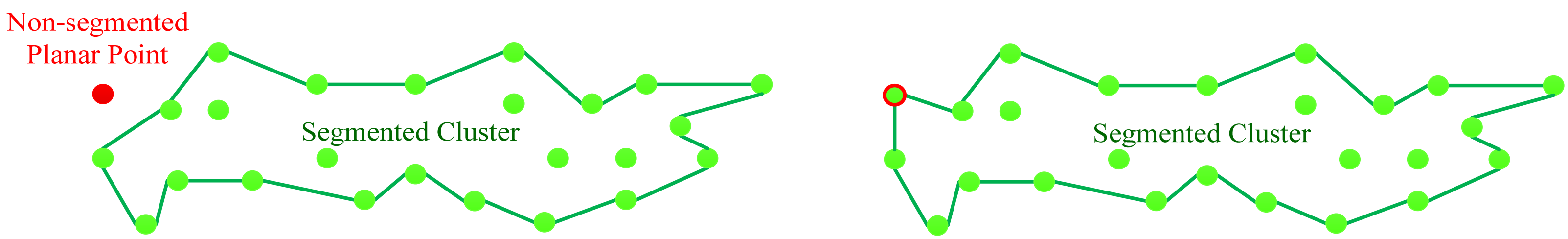
Quality Control of LiDAR Data Segmentation

- **Objective:** Establish a procedure to evaluate the quality of the outcome from the segmentation process
- Issues that should be addressed by the quality control procedure:
  - Ability to check if there is something wrong in the segmentation procedure
  - Ability to fix what is wrong
- Quality control procedure:
  - Hypothesize different scenarios/problems in the segmentation results
  - Develop procedures for detecting/identifying these problems
  - Suggest possible actions to remedy these problems

Quality Control of LiDAR Data Segmentation

- Hypothesized segmentation problems:

1. **Non-segmented planar points**: Points, which have been classified as being part of planar surfaces, are not segmented in any of the detected clusters.



- For this scenario, the quality control measure will be derived as follows:

$$\boxed{QC - measure_1 = \frac{m}{n}} \longrightarrow \text{The smaller, the better}$$

where,

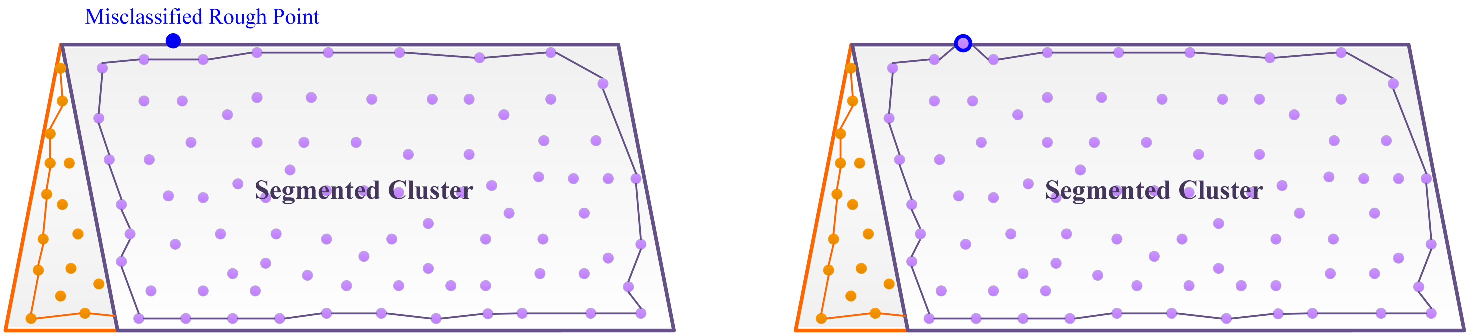
m = the number of non-segmented planar points that have been incorporated into the segmented regions as a result of the proposed quality control procedure

n = the total number of non-segmented planar points

Quality Control of LiDAR Data Segmentation

- Hypothesized segmentation problems:

2. **<u>Non-segmented rough points</u>**: Points, which have been classified as being part of rough surfaces, might belong to one of the segmented planar regions (i.e., some of the classified rough points are erroneously classified).



- For this scenario, the quality control measure will be derived as follows:

where, $$\boxed{QC-measure_2=\frac{m}{n}}$$ $\longrightarrow$ The smaller, the better

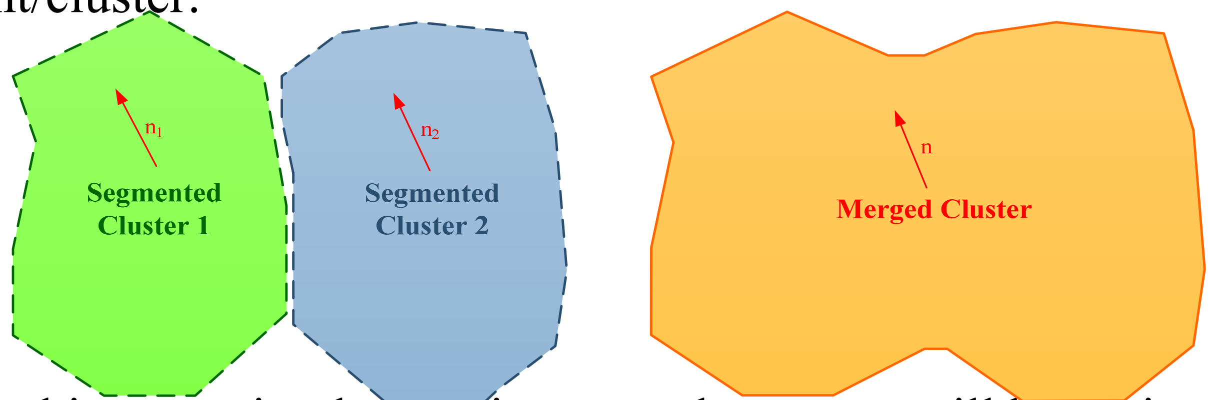
m = the number of rough points that have been incorporated into the segmented regions as a result of the proposed quality control procedure

n = the total number of rough points

Quality Control of LiDAR Data Segmentation

- Hypothesized segmentation problems:

3. **<u>Over-segmentation</u>:** A planar surface is segmented into more than one segment/cluster.



- For this scenario, the quality control measure will be derived as follows:

where, $\boxed{QC-measure_3 = \frac{m}{n}}$ → The smaller, the better

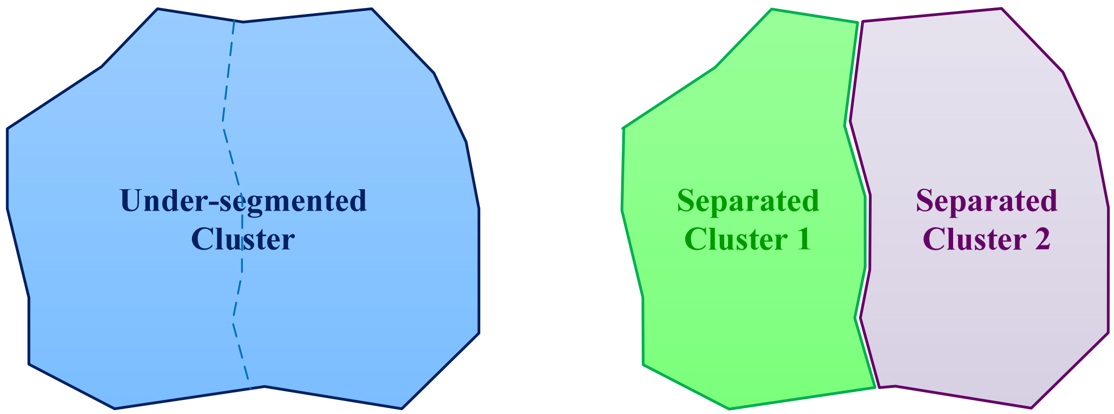
m = the number of regions that have been incorporated into other regions as a result of proposed quality control procedure

n = the total number of segmented regions

Quality Control of LiDAR Data Segmentation

- Hypothesized segmentation problems:

4. **Under-segmentation:** Two or more planar surfaces are segmented into one segment/cluster.



- For this scenario, the quality control measure will be derived as follows:

where, $\boxed{QC-measure_4 = \frac{m}{n}}$ $\longrightarrow$ The smaller, the better

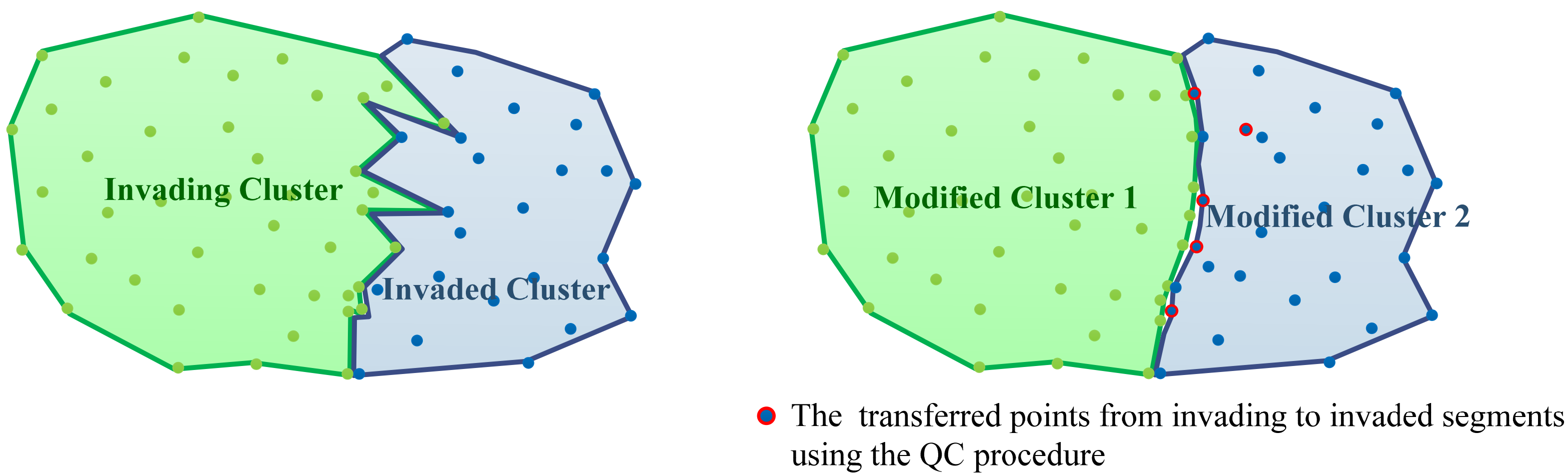
m = the number of regions that have been split into several region

n = the total number of segmented regions

Quality Control of LiDAR Data Segmentation

- Hypothesized segmentation problems:

5. **Invading/Invaded segments:** One segment is invading/being invaded by another segment.



- For this scenario, the quality control measure will be derived as follows:

where,

$$\boxed{QC - measure_5 = \frac{m_i}{n_p}} \longrightarrow \text{The smaller, the better}$$

m_i = the total number of points that have been transferred from invading to invaded segments

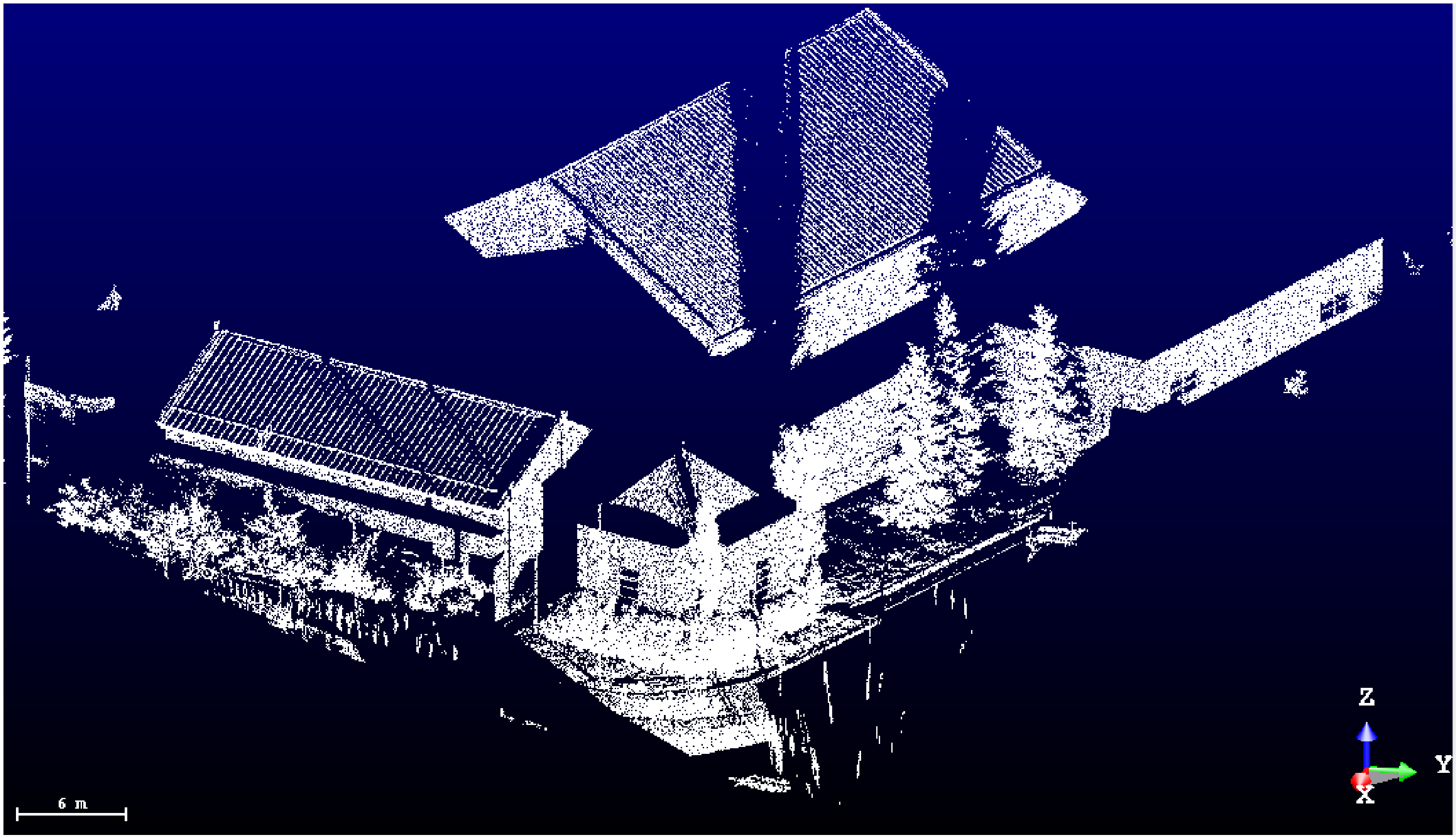
n_p = the total number of points in segmented regions

Segmentation Experimental Results

- Data used: A multi-platform LiDAR dataset from the Rozsa Center, University of Calgary, containing:
  - Six tripod mounted scans averaging (200 *pts/m²*)
  - Three airborne laser scans (~ 3 *pts/m²*)

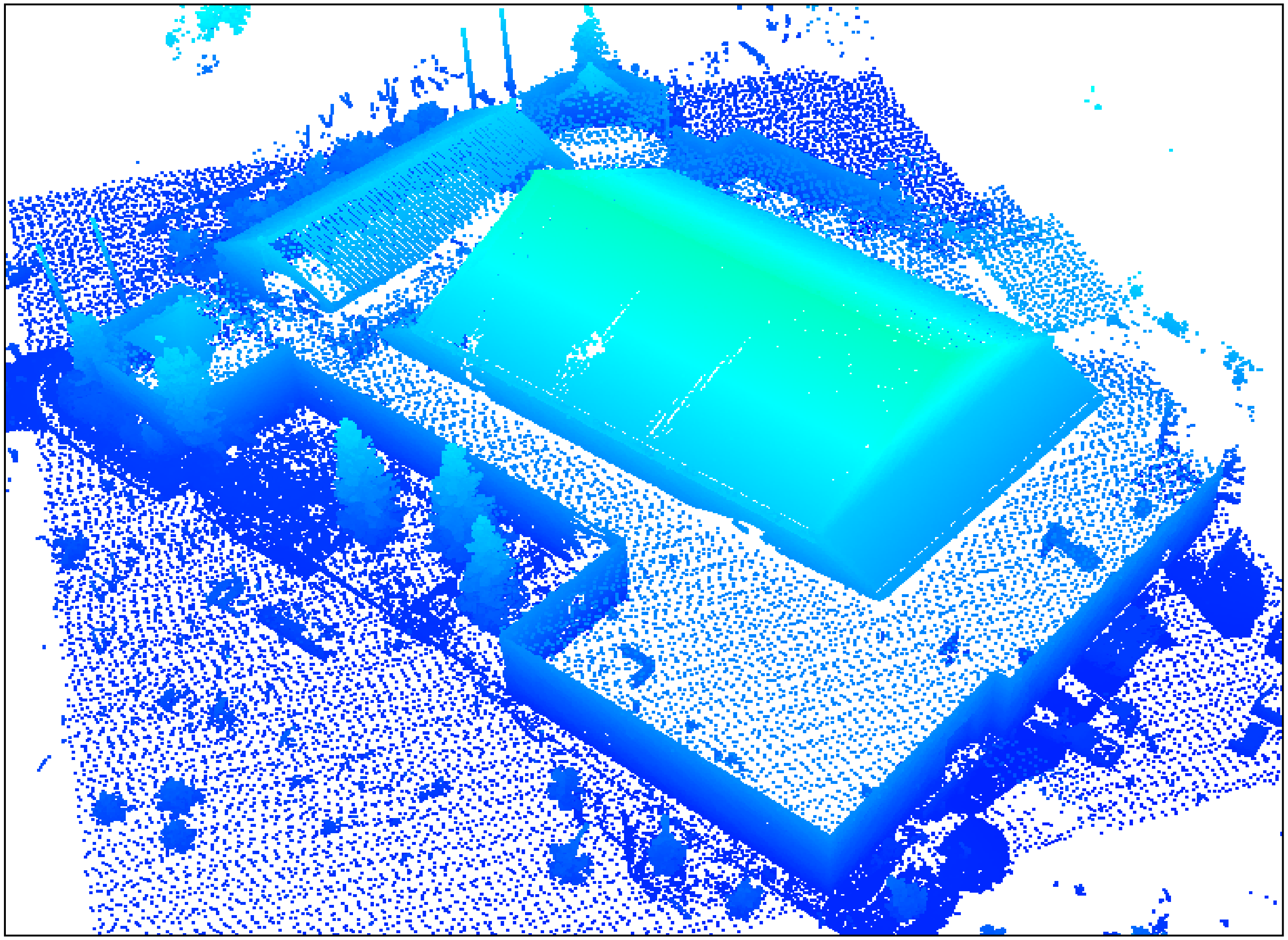
Segmentation Experimental Results

Segmentation Experimental Results



Segmentation Experimental Results

Registered multi-platform LiDAR Dataset



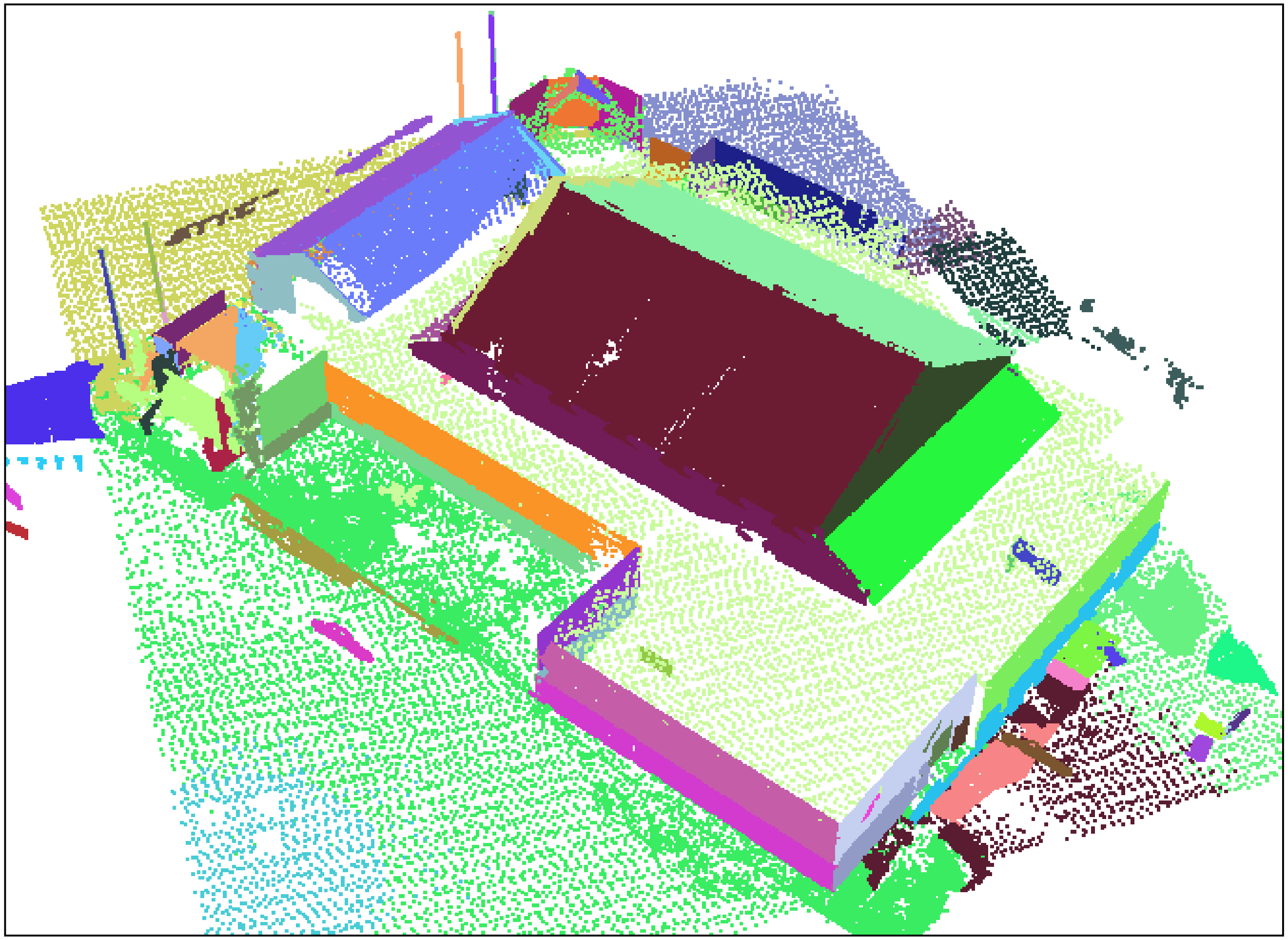
Segmentation Experimental Results

Pre-defined Segmentation Thresholds

Threshold	Value
Noise level in airborne LiDAR datasets	20 cm
Noise level in terrestrial LiDAR datasets	2 cm
Number of points for reliable plane definition	12 points
$\Delta\alpha$	10°
Δd	5 cm
Size of minimum detectable cluster	25 points

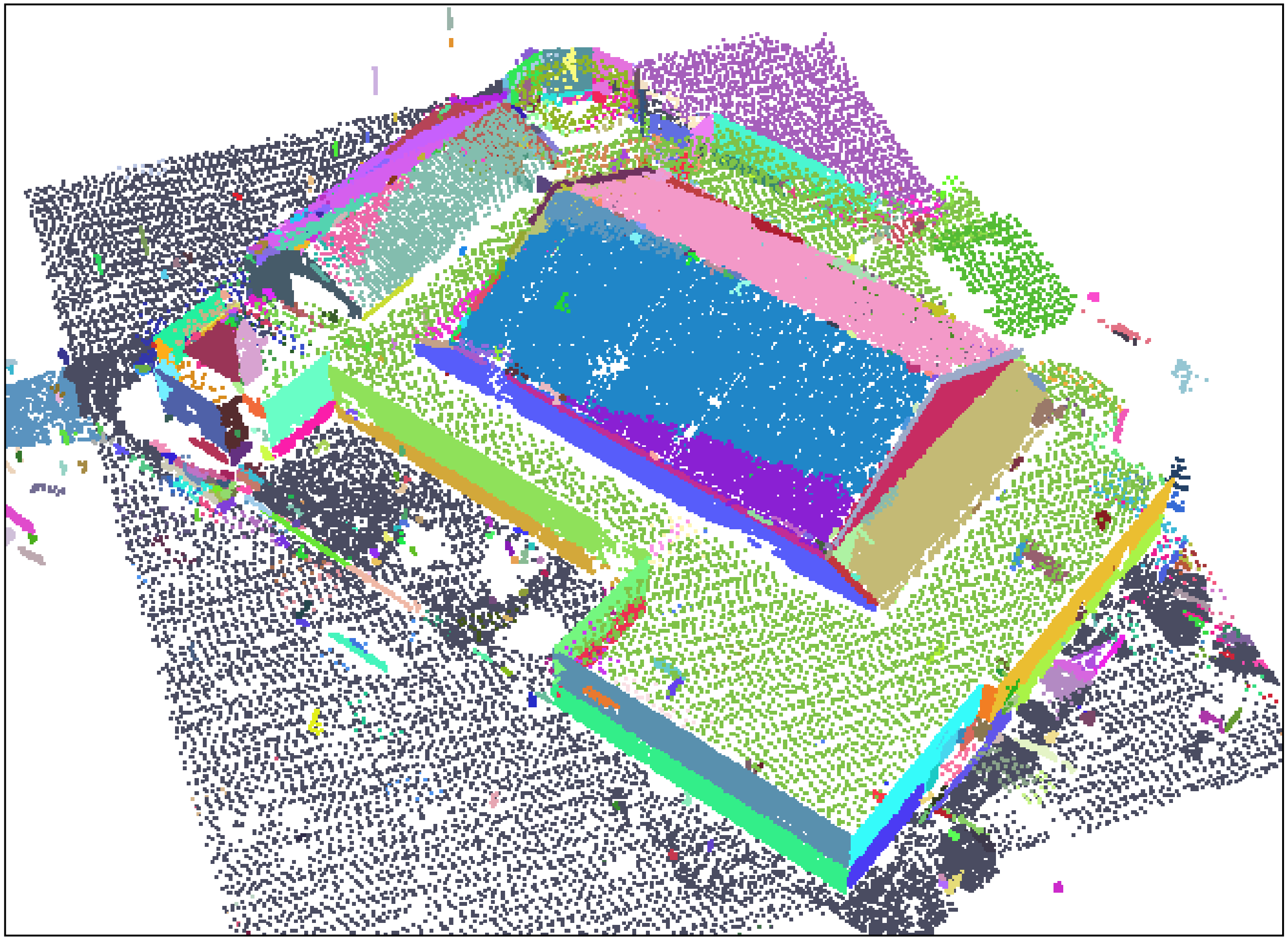
Segmentation Experimental Results

Spatial-domain segmentation result



Segmentation Experimental Results

Parameter-domain segmentation result



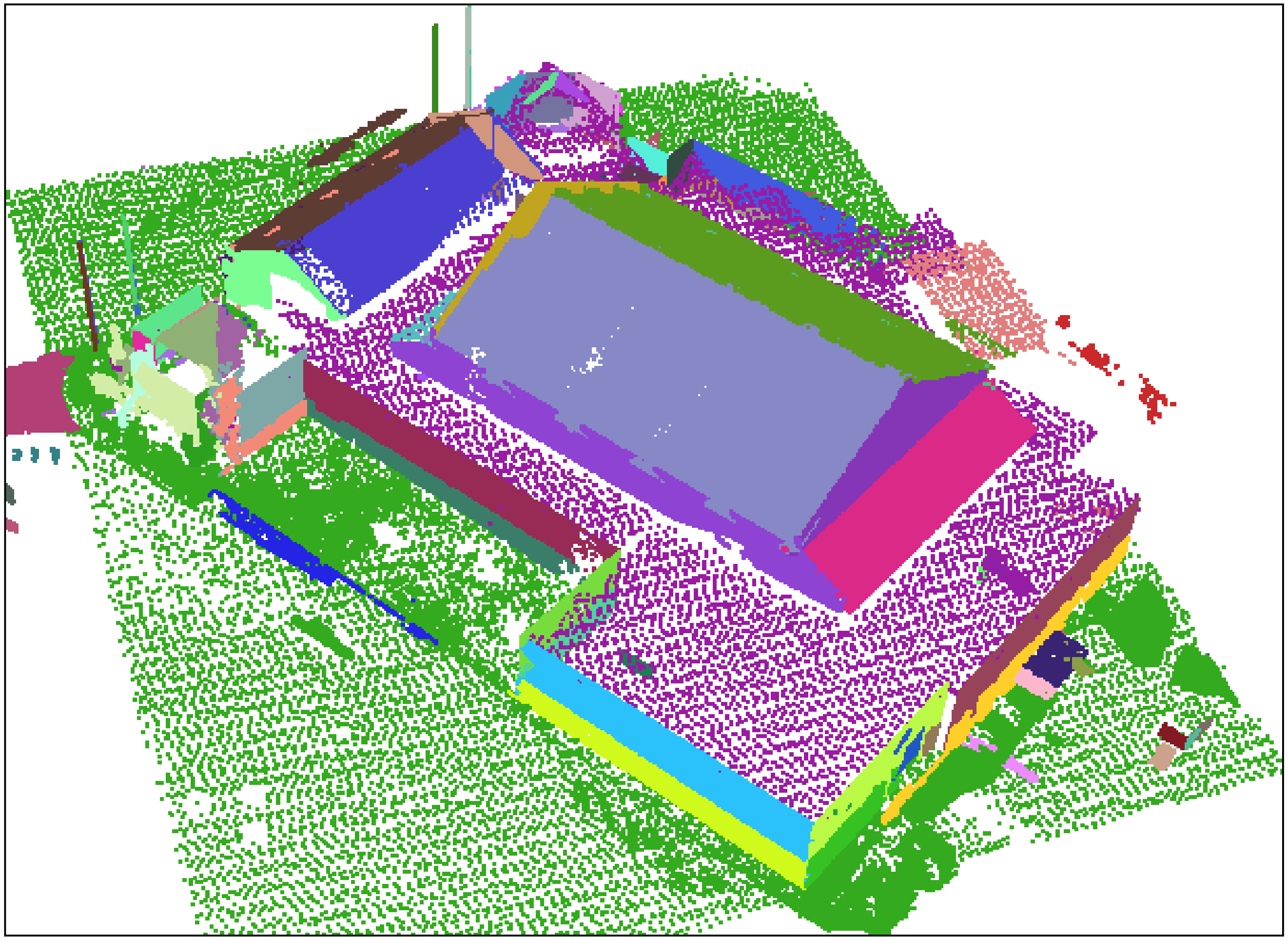
Segmentation Experimental Results

Comparative analysis of spatial-domain and parameter-domain LiDAR data segmentation results

Quality control measures	Spatial-domain segmentation results	Parameter-domain segmentation results
Non-segmented planar points	N/A	18%
Misclassified non-planar points	14%	5%
Over-segmentation	11%	14%
Under-segmentation	1%	0.8%
Invading/Invaded segments	0%	0%

Segmentation Experimental Results

Segmentation outcome after quality control procedure

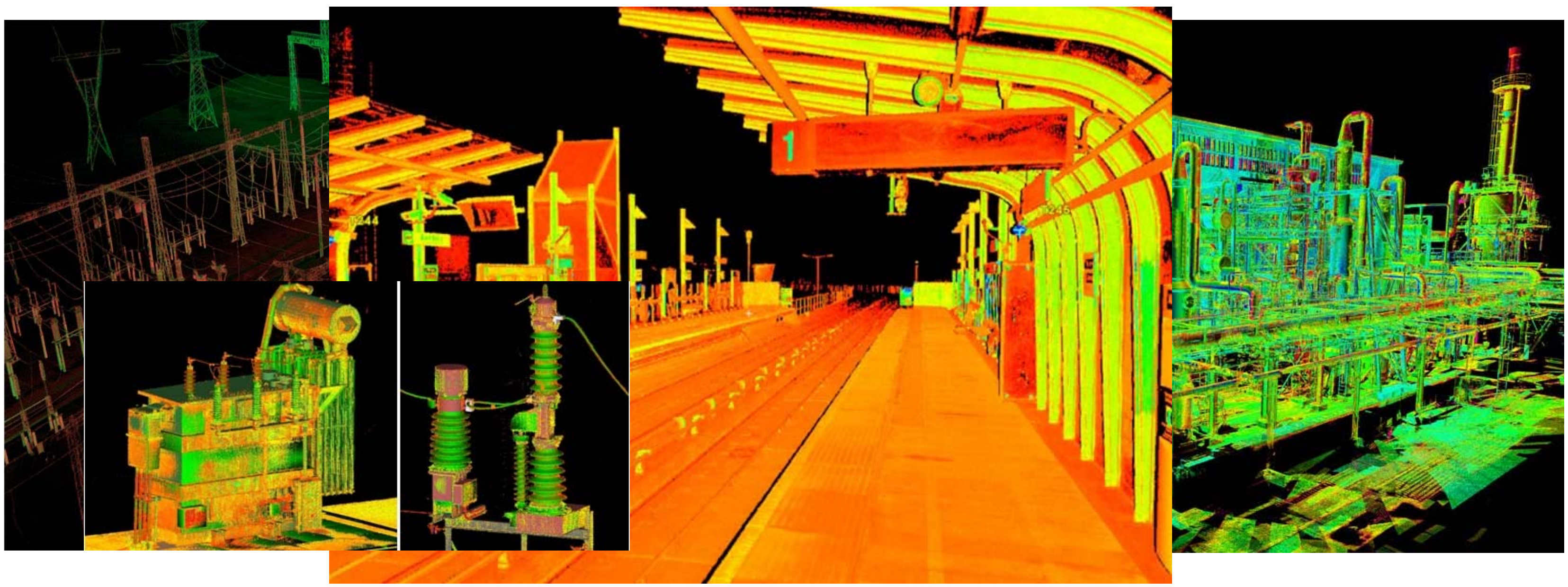


LiDAR Data Segmentation

Linear Segmentation

Linear Feature Segmentation

- Detection and segmentation of **linear/cylindrical** features in laser scanning data
  - Light, traffic, and flag poles
  - Pipelines
  - Electrical transmission lines
  - Electrical transformers and surge arresters

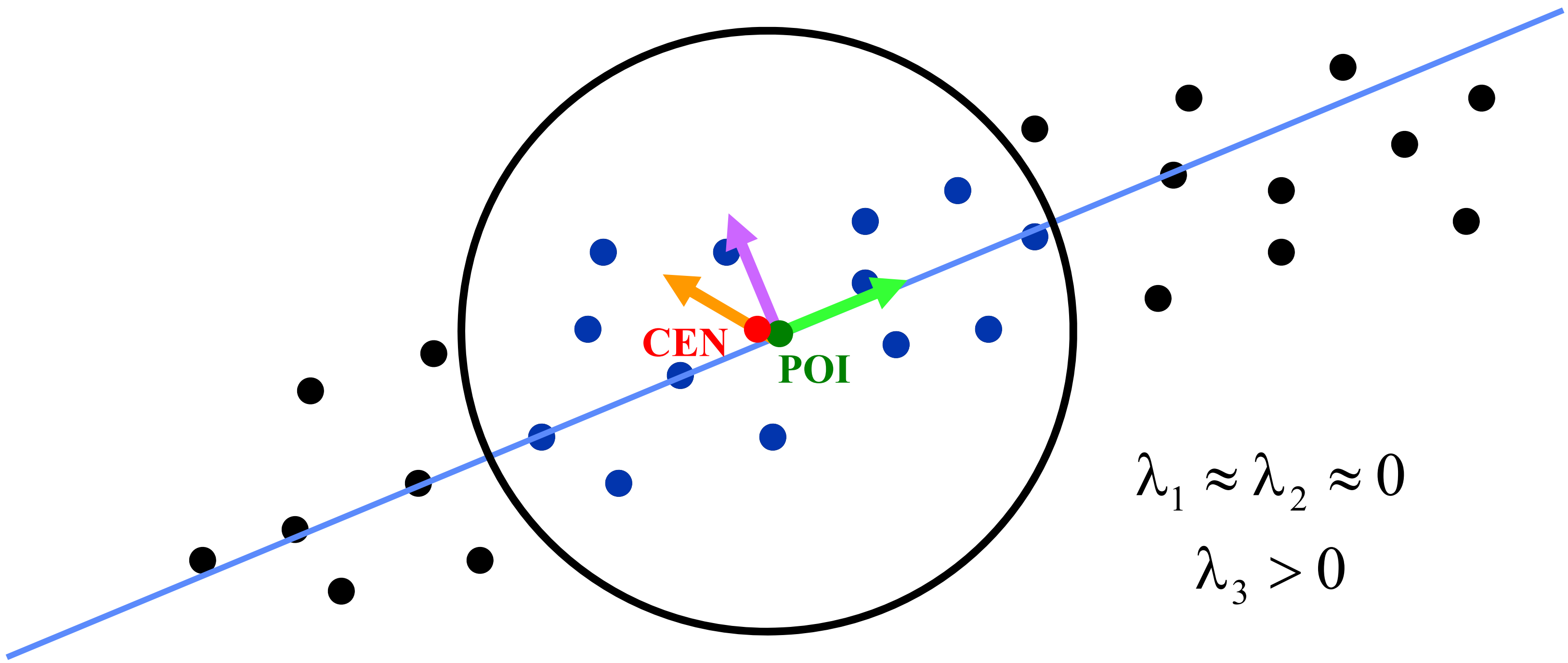


Linear Feature Segmentation: Literature

- Detection and segmentation of **linear/cylindrical** features in laser scanning data
  - Covariance analysis of each point by analysing the Eigen values of the symmetric 3 by 3 matrix containing the centralised 2^{nd} order moments (Belton and Lichti, 2006; Gross and Thoennessen, 2006)
  - Feature line growing approach based on one manually selected seed points or seed segments (Briese, 2006)
  - Extraction of intersection line or boundary lines of segmented planar patches (Briese and Pfeifer, 2008)
  - Hough transform based on estimated orientation, position, and radius parameters (Rabbani and van den Heuvel, 2005)

Linear-Feature-Based Point Classification

- Eigen-value Analysis for the classification of points belonging to linear features



$$\lambda_1 \approx \lambda_2 \approx 0$$
$$\lambda_3 > 0$$

  – Eigen vector $\vec{e}_3$ is along the direction of the line

Linear-Feature-Based Point Classification

- Eigen-value Analysis for the classification of points belonging to linear features
  - Calculate the dispersion matrix for the points in the spherical neighborhood relative to the centroid point

$$C_{3\times 3} = \frac{1}{k+1}\sum_{i=1}^{k+1}(\vec{r}_i - \vec{r}_{Centroid})(\vec{r}_i - \vec{r}_{Centroid})^T$$

$$\vec{r}_i = \begin{bmatrix} X_i & Y_i & Z_i \end{bmatrix}^T$$

$$\vec{r}_{Centroid} = \frac{1}{k+1}\sum_{i=1}^{k+1}\vec{r}_i$$

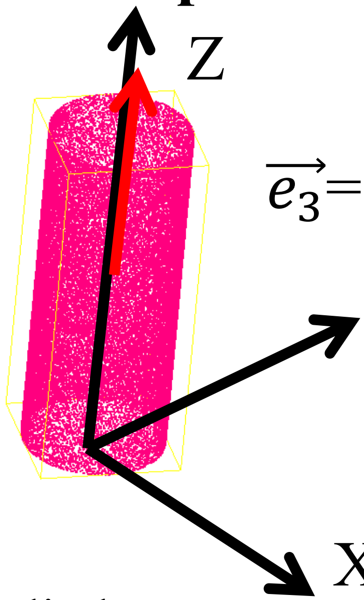
  - Eigen value decomposition of the dispersion matrix

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

If $\lambda_1 \approx \lambda_2 \approx 0$ and $\lambda_3 > 0$, the point of interest (POI) is considered to belong to a linear/cylindrical surface.

Linear-Feature-Based Point Classification

- **Principal component analysis (PCA)**



$\overrightarrow{e_3}$=(0, 0, 1)

Cylinder Parameters:
$X_0, Y_0, Z_0 = 0$
$ux, uy = 0,\ uz = 1,\ r = 4$

71441 Point, Z=(1:20)
$\vec{r}_{Centroid}$ = (0, 0, 10)

$8.02(\lambda_1)$	0	0
0	$8.02(\lambda_2)$	0
0	0	$32.99(\lambda_3)$

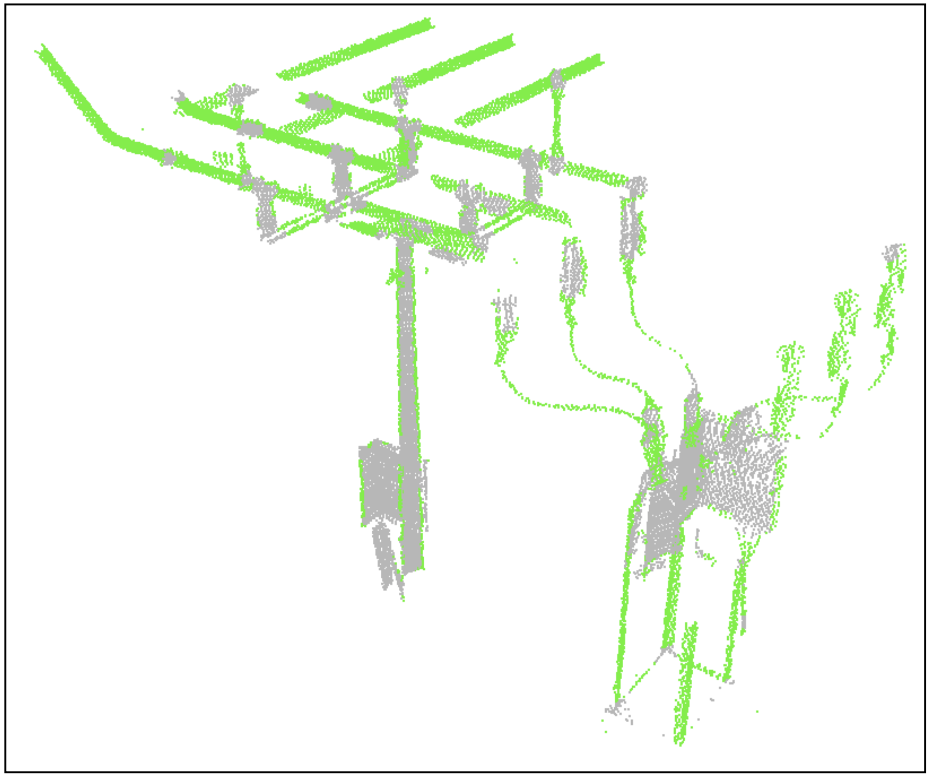
Λ Matrix

$\overrightarrow{e_1}$	$\overrightarrow{e_2}$	$\overrightarrow{e_3}$
1.0	0.0	0.0
0.0	1.0	0.0
0.0	0.0	1.0

W Matrix

Linear-Feature-Based Point Classification

- **Principal component analysis (PCA)**



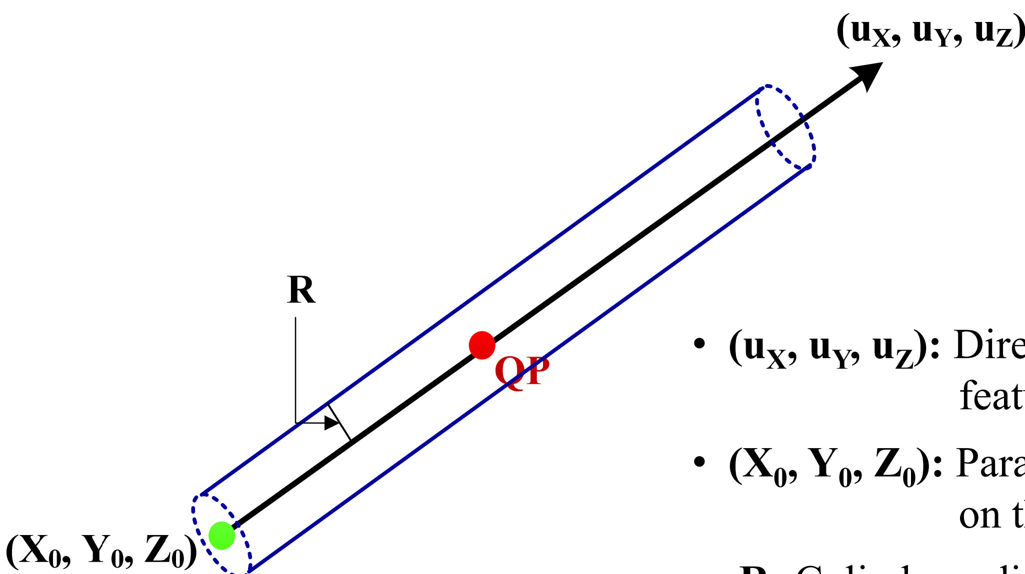
Neighborhood size:
Nearest 50 points

Points satisfy $\frac{\lambda_3}{(\lambda_1+\lambda_2+\lambda_3)} > 0.70$

Linear Feature Representation

- Representation of classified linear/cylindrical features
  - Typical representation form for a linear/axis of cylindrical feature

$$\begin{cases} X = u_X t + X_0 \\ Y = u_Y t + Y_0 \\ Z = u_Z t + Z_0 \end{cases}$$



- **(u_X, u_Y, u_Z):** Directional parameters of linear/cylindrical features
- **(X_0, Y_0, Z_0):** Parameters defining the position of a point on the best-fitted line/cylinder
- **R:** Cylinder radius

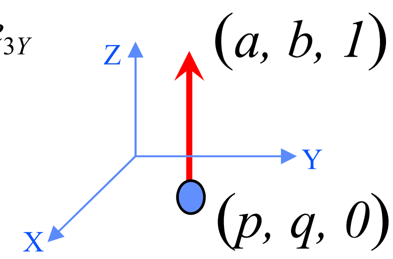
Linear Feature Representation

- Selection of appropriate representation form for linear features
  - Avoid singularities in linear feature representation

1. Linear/cylindrical features $\nparallel$ to XY-plane:

$$\begin{cases} X = at + p \\ Y = bt + q \\ Z = t \end{cases}$$

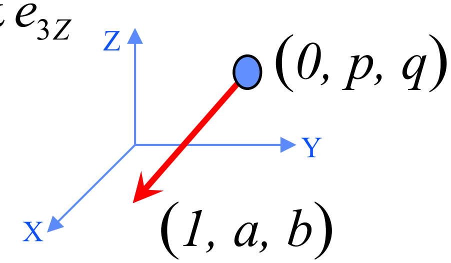
$e_{3Z} > e_{3X}$ & e_{3Y}



2. Linear/cylindrical features $\nparallel$ to YZ-plane:

$$\begin{cases} X = t \\ Y = at + p \\ Z = bt + q \end{cases}$$

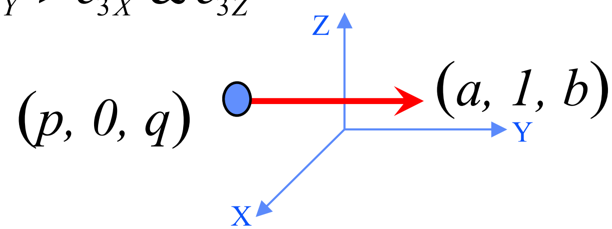
$e_{3X} > e_{3Y}$ & e_{3Z}



3. Linear/cylindrical features $\nparallel$ to XZ-plane:

$$\begin{cases} X = at + p \\ Y = t \\ Z = bt + q \end{cases}$$

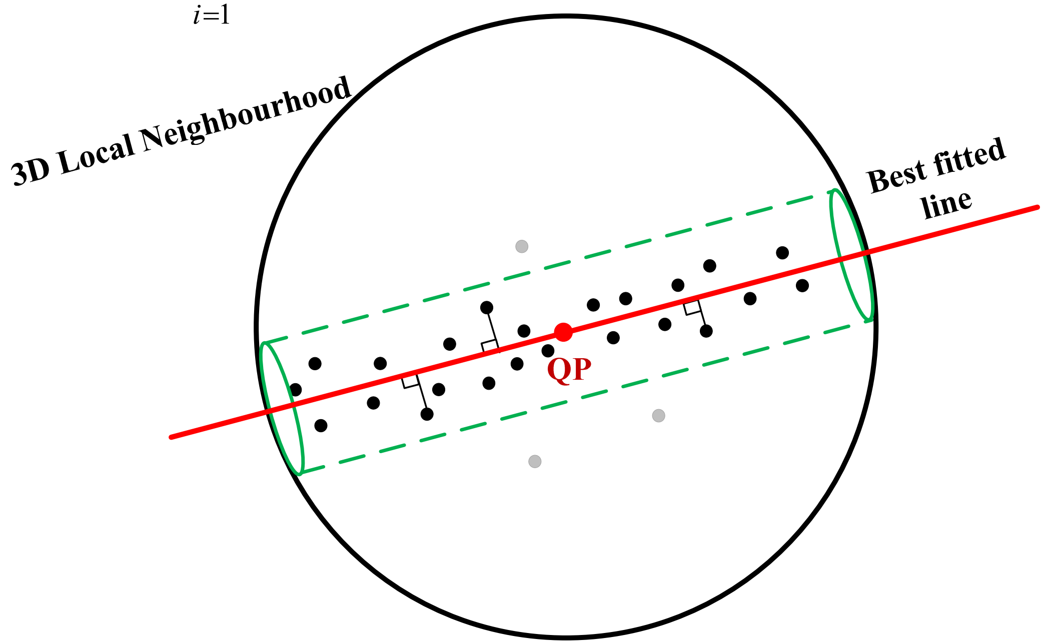
$e_{3Y} > e_{3X}$ & e_{3Z}



Linear Feature Parameter Estimation

- Precise estimation of linear/cylindrical features attributes
  - Adaptive cylinder neighborhood definition: minimizing the squared sum of the normal distances between the points in the established 3D neighborhood and the linear/cylindrical feature in question

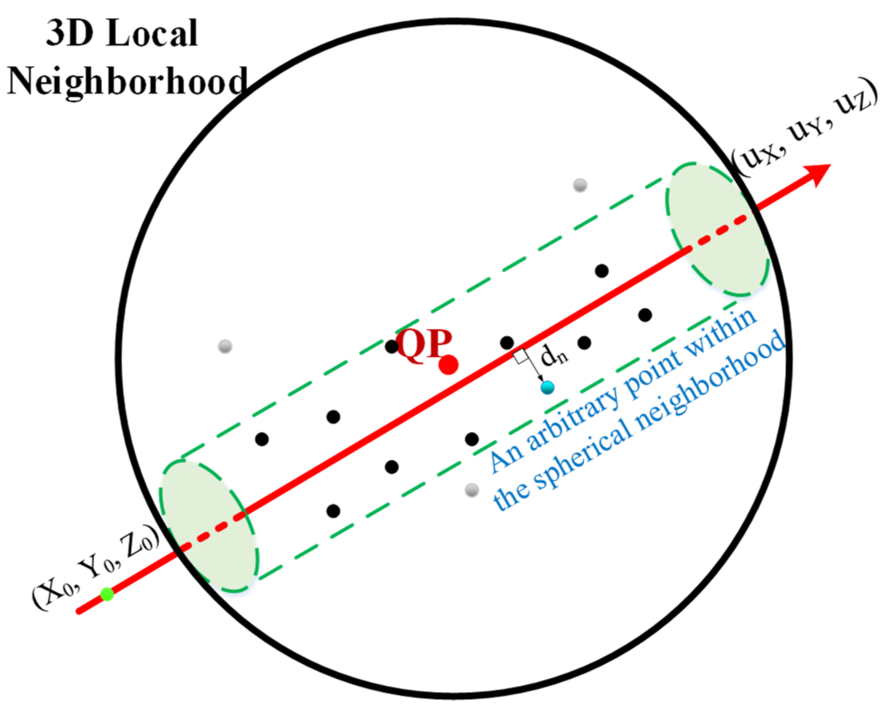
$$\sum_{i=1}^{n} w_i^2 d_{n_i}^2 = \min(u_X, u_Y, u_Z, X_0, Y_0, Z_0, R)$$



Linear Feature Characterization

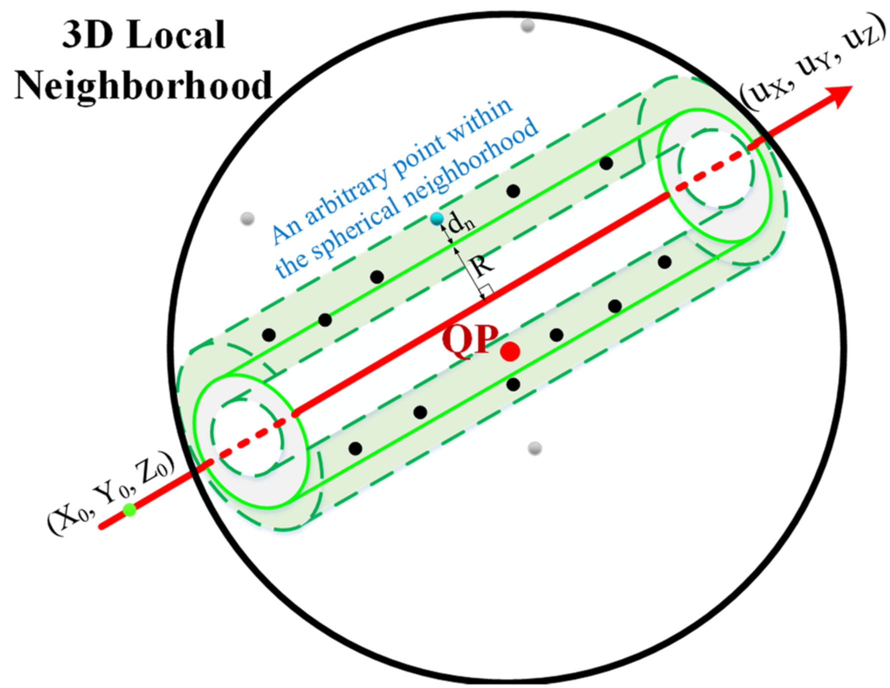
- Local point density estimation along linear/cylindrical features

Points along linear features



$$LPD\ (\text{pnts/m}) = \frac{k}{2r_n}$$

Points along cylindrical features



$$LPD\ (\text{pnts/m}^2) = \frac{k}{4\pi R r_n}$$

Spatial-Domain Linear Feature Segmentation

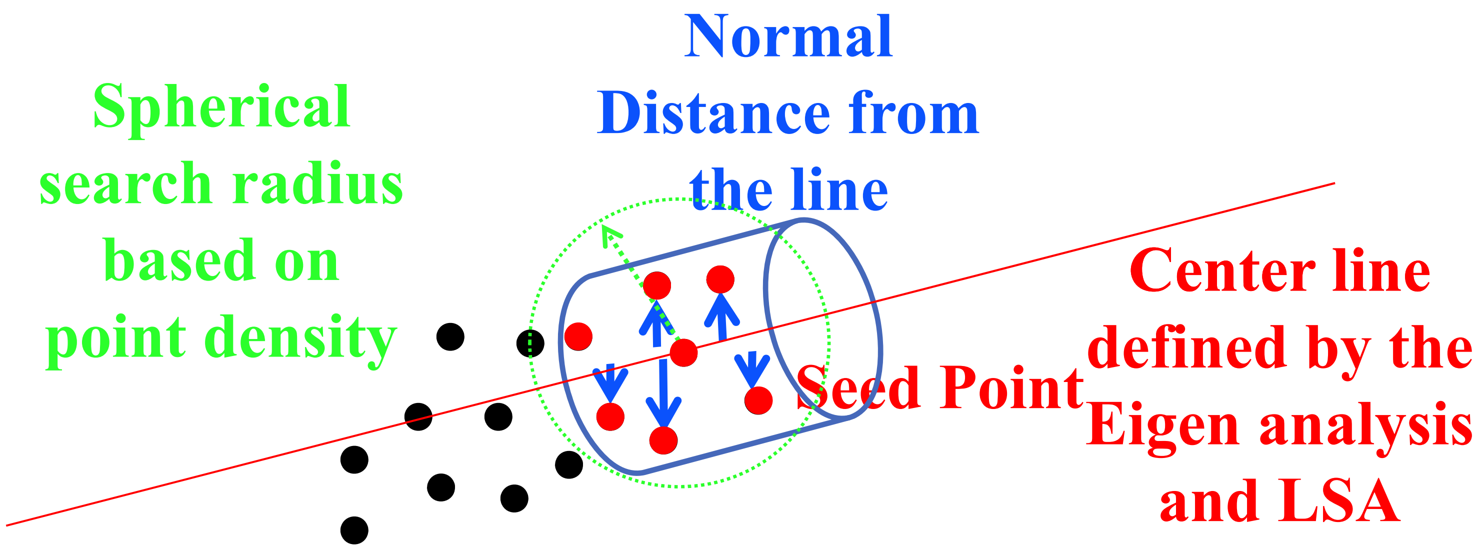
Initial classification of linear features using Eigen-value analysis

Selection of the appropriate representation of the classified linear features

Precise estimation of linear features' parameters using generalized LSA

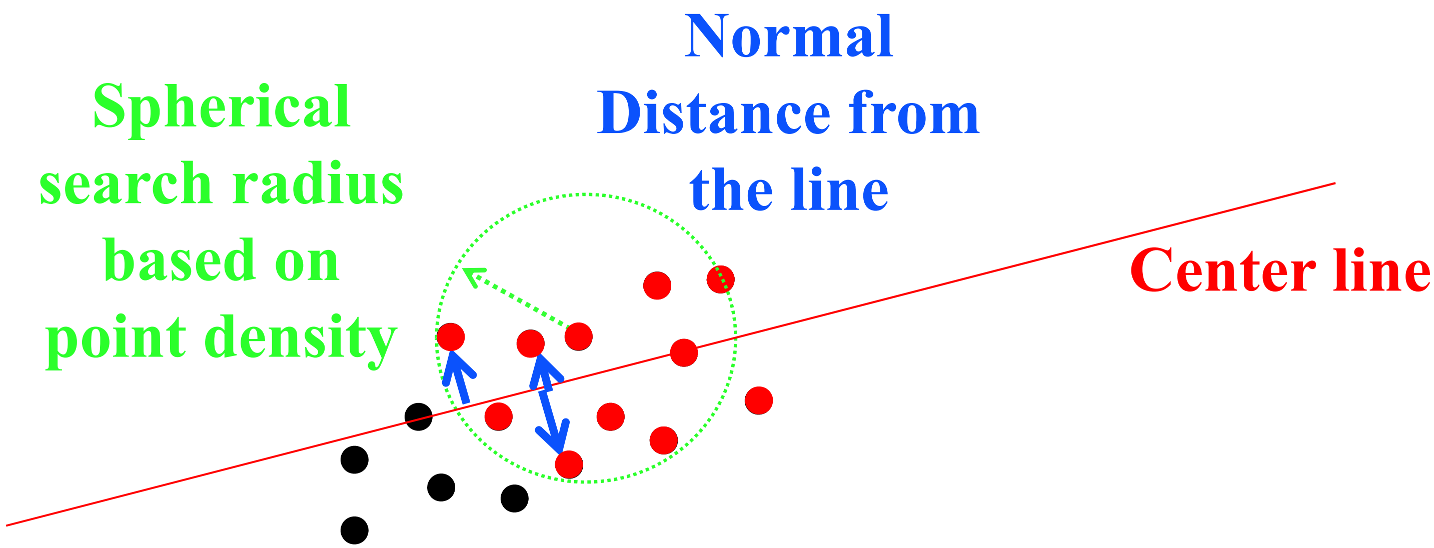
Spatial-domain segmentation of linear/cylindrical features starting from the seed points that have been defined by the Eigen value/LSA analysis

Spatial-Domain Linear Feature Segmentation



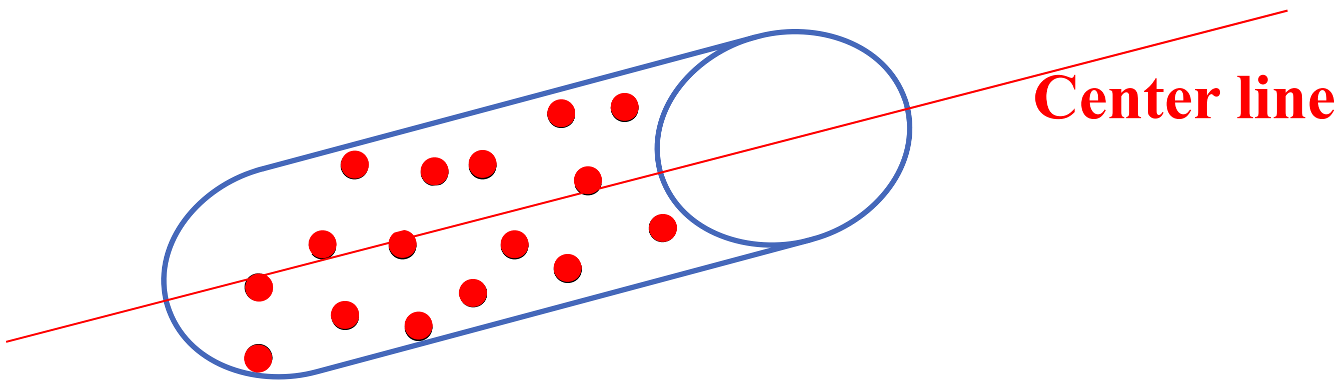
All classified points will be used to re-estimate line/ cylinder parameters

Spatial-Domain Linear Feature Segmentation



The same search/check criteria will be performed starting from each classified point

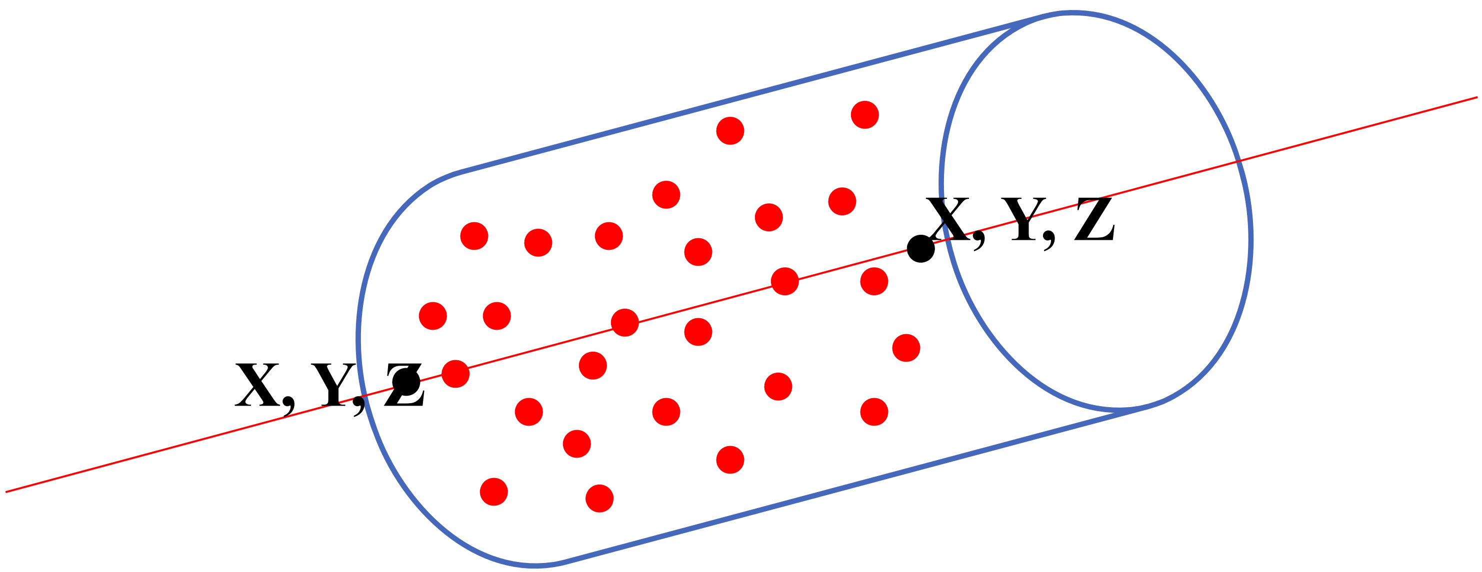
Spatial-Domain Linear Feature Segmentation



The same search/check criteria will be performed starting from each classified point

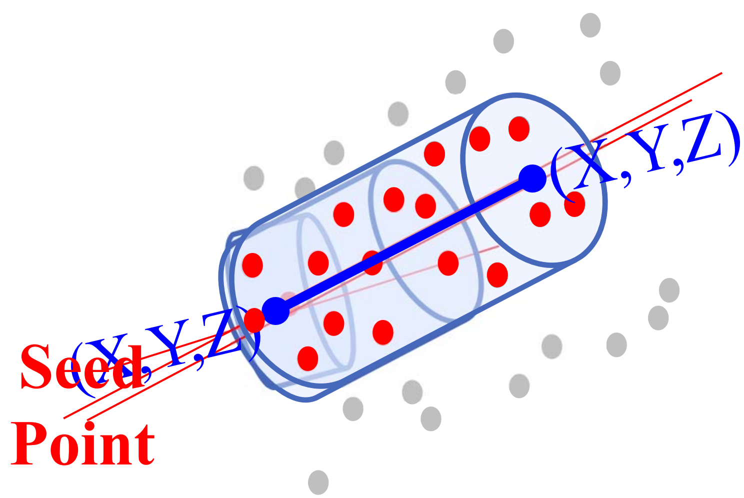
Spatial-Domain Linear Feature Segmentation

Classified points will be projected onto the best defined line to determine the line extreme points



Spatial-Domain Linear Feature Segmentation

Region growing methodology for the extraction of linear features from the scans



The search radius is based on the estimated LPD.

Parameter-Domain Linear Feature Segmentation

Initial classification of linear features using Eigen-value analysis

Selection of the appropriate representation of the classified linear features

Precise estimation of linear features' parameters using generalized LSA

Parameter-domain segmentation for isolation of points belonging to linear/cylindrical features

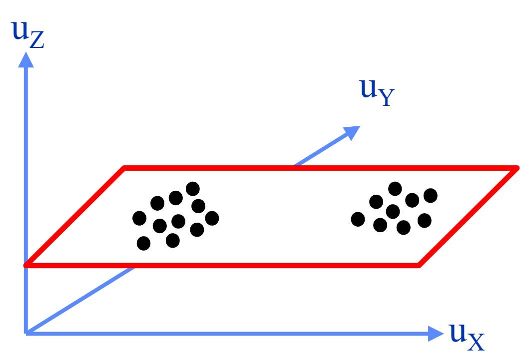
Parameter-Domain Linear Feature Segmentation

- Segmentation of the linear/cylindrical features in the parameter domain (u_X, u_Y, u_Z, X_0, Y_0, Z_0)
  - In order to avoid computational explosion for the 6 dimensional parameter space, we try to compute the directional/point-along-line peaks for each line representation form.

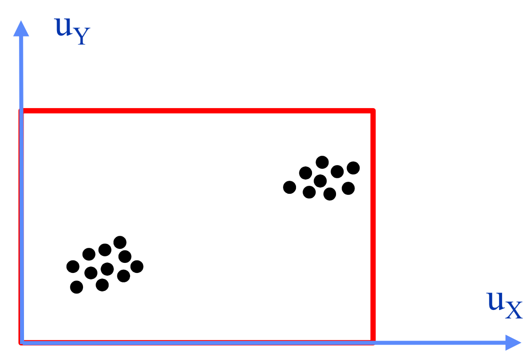
Lines not parallel to XY-plane	Lines not parallel to YZ-plane	Lines not parallel to XZ-plane
Peaks in u_X/u_Y space	Peaks in u_Y/u_Z space	Peaks in u_X/u_Z space
↓	↓	↓
Peaks in X_0/Y_0 space	Peaks in Y_0/Z_0 space	Peaks in X_0/Z_0 space

Parameter-Domain Linear Feature Segmentation

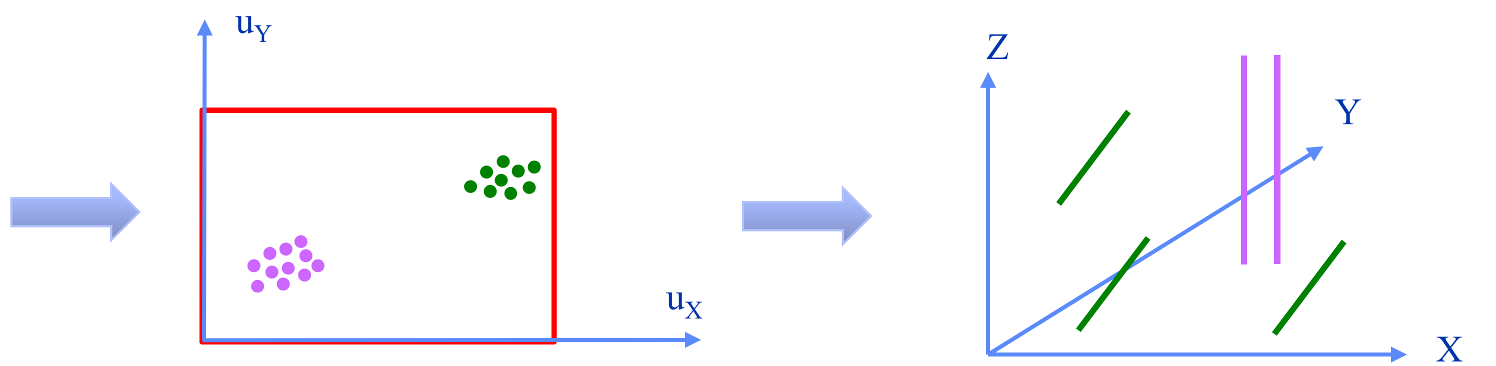
- Clustering the attributes in the parameter domains for a given representation form:
  - Linear/cylindrical features which are not parallel to XY-plane



3D directional parameter domain

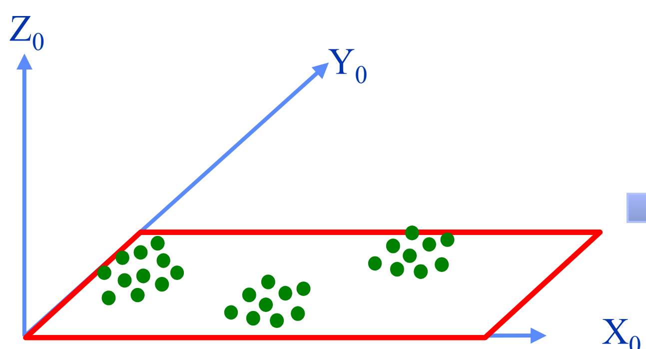


2D directional parameter domain

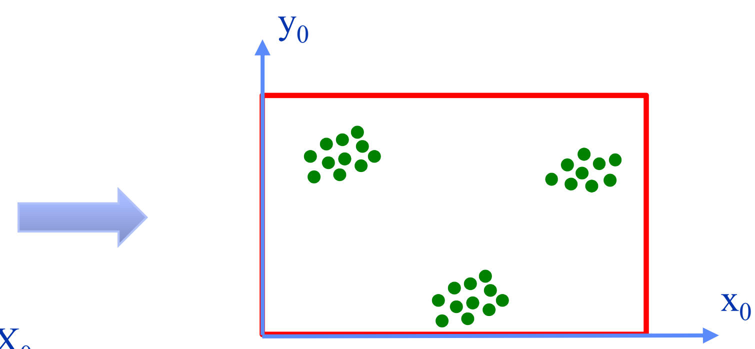


Parameter-Domain Linear Feature Segmentation

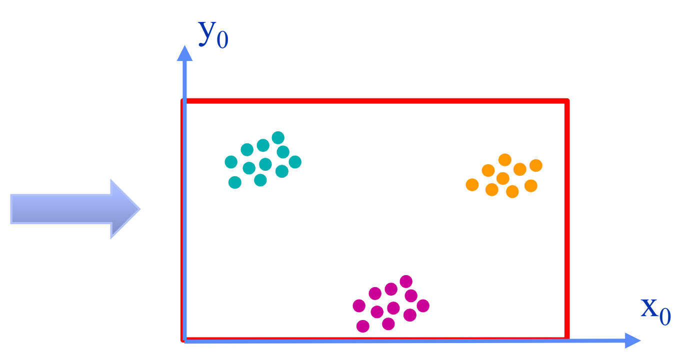
- Clustering the attributes in the parameter domains for a given representation form:
  - Linear/cylindrical features which are not parallel to XY-plane

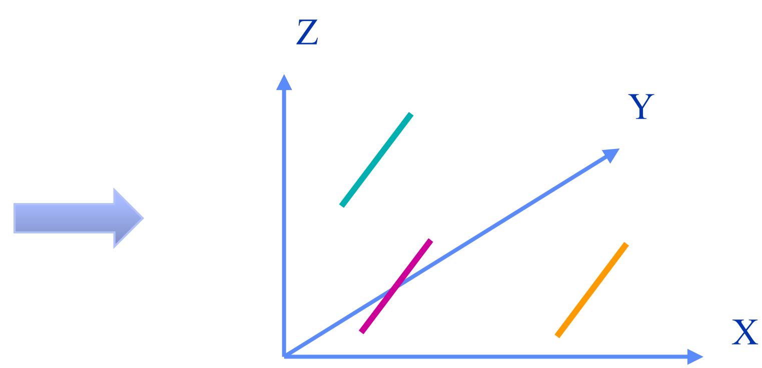


3D point-along-line parameter domain



2D point-along-line parameter domain





Quality Control of Linear Feature Segmentation

Linear Feature Segmentation

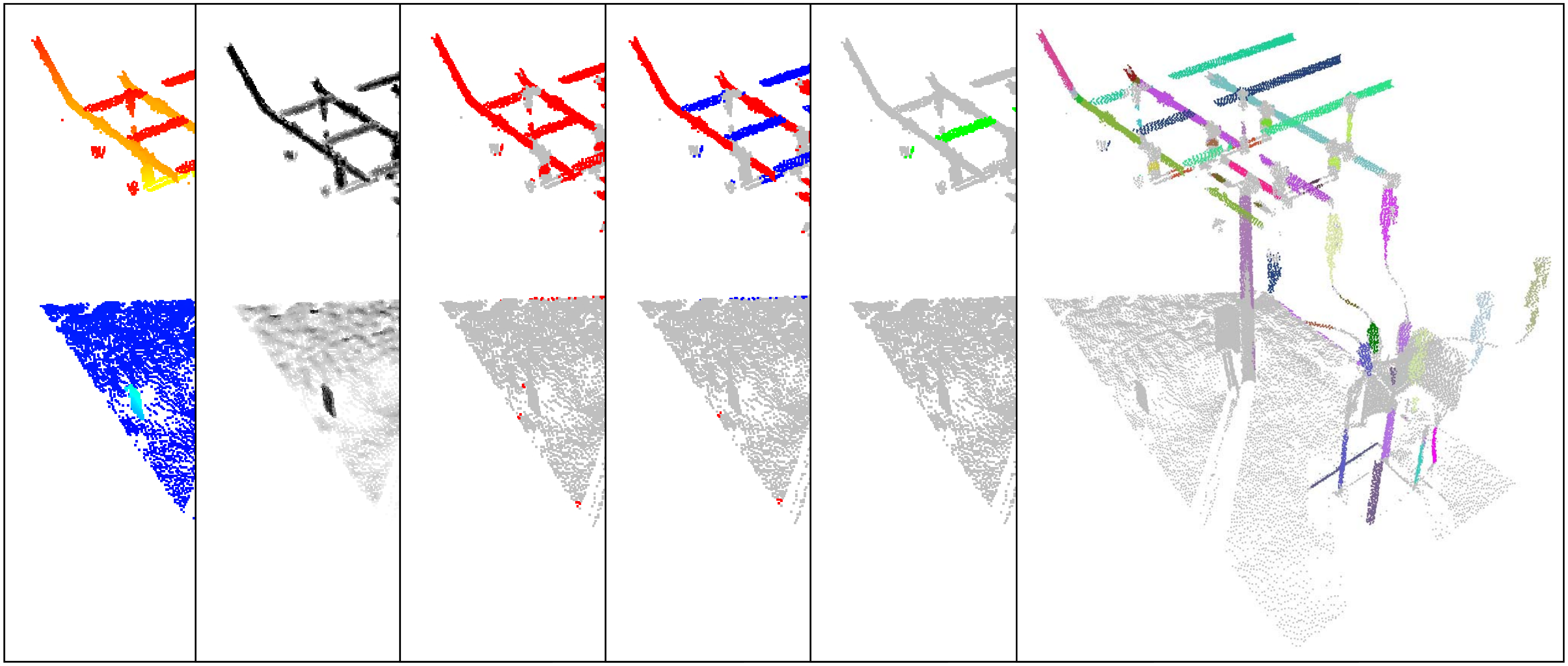
QC of Linear Feature Segmentation

- Objective: Establish a procedure to evaluate the quality of the outcome from the segmentation process
- Issues that should be addressed by the quality control procedure:
  - Ability to check if there is something wrong in the segmentation procedure
  - Ability to fix what is wrong
- Quality control procedure:
  - Hypothesize different scenarios/problems in the segmentation results
  - Develop procedures for detecting/identifying these problems
  - Suggest possible actions to remedy these problems

Potential Segmentation Problems

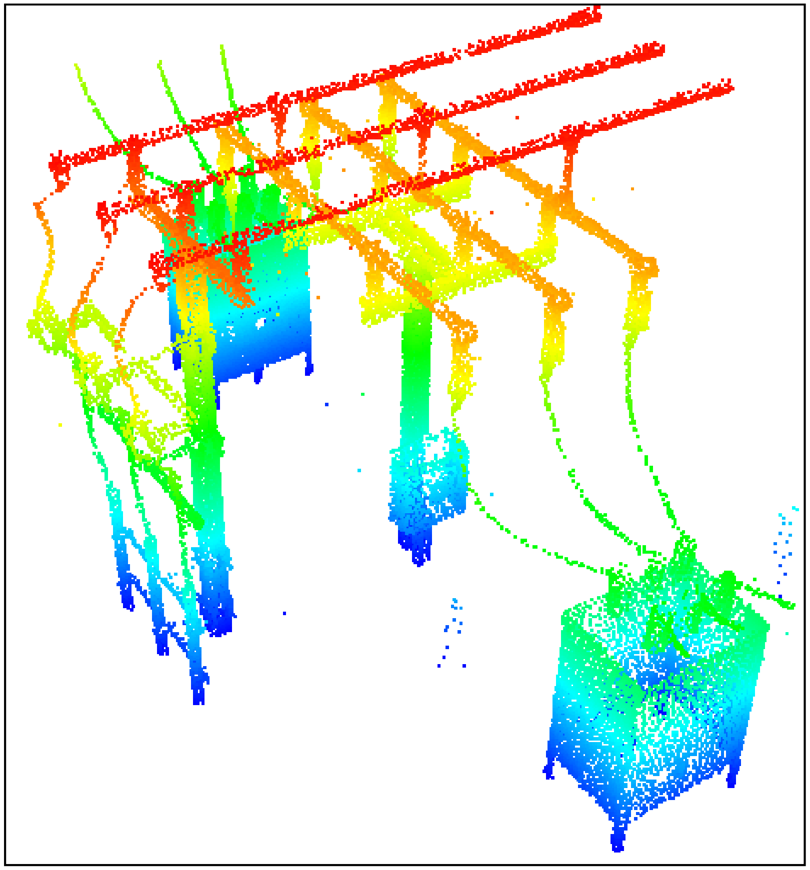
- Hypothesized segmentation problems:
  1. **<u>Non-segmented linear/cylindrical points</u>**: Points, which have been classified as being part of linear/cylindrical features, are not segmented in any of the detected clusters.
  2. **<u>Non-segmented rough points</u>**: Points, which have been classified as being part of rough surfaces, might belong to one of the segmented linear/cylindrical features (i.e., some of the classified rough points are erroneously classified).
  3. **<u>Over-segmentation</u>**: A linear/cylindrical feature is segmented into more than one segment/cluster.
  4. **<u>Under-segmentation</u>**: Two or more linear/cylindrical features are segmented into one segment/cluster.

Linear Features Segmentation Results (1)

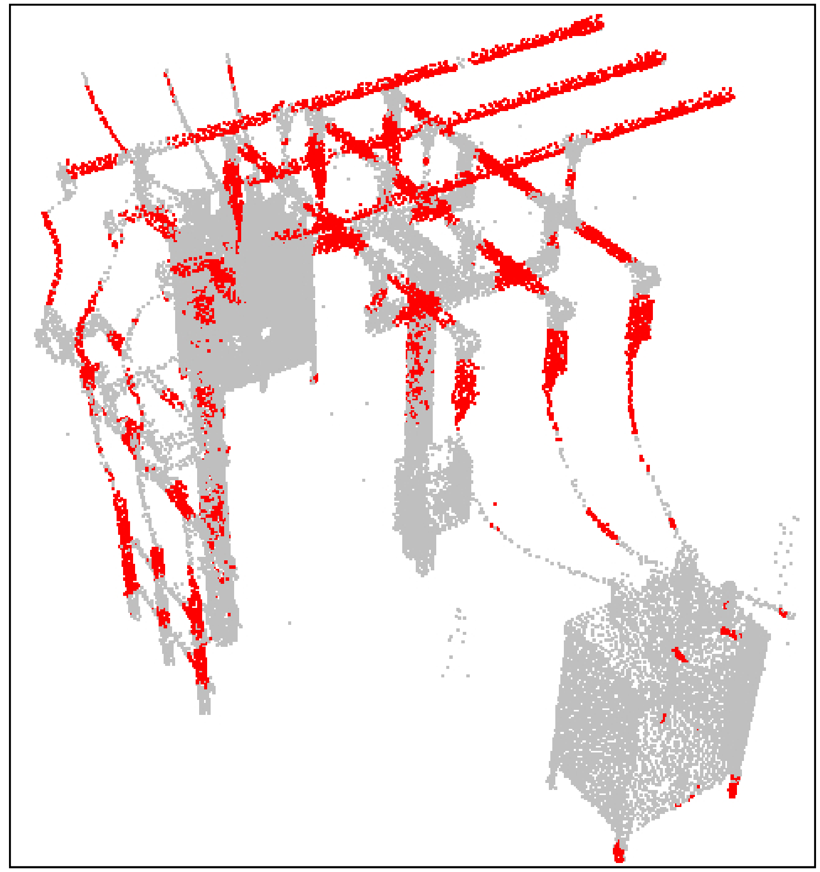


Original

Linear Features Segmentation Results (1)

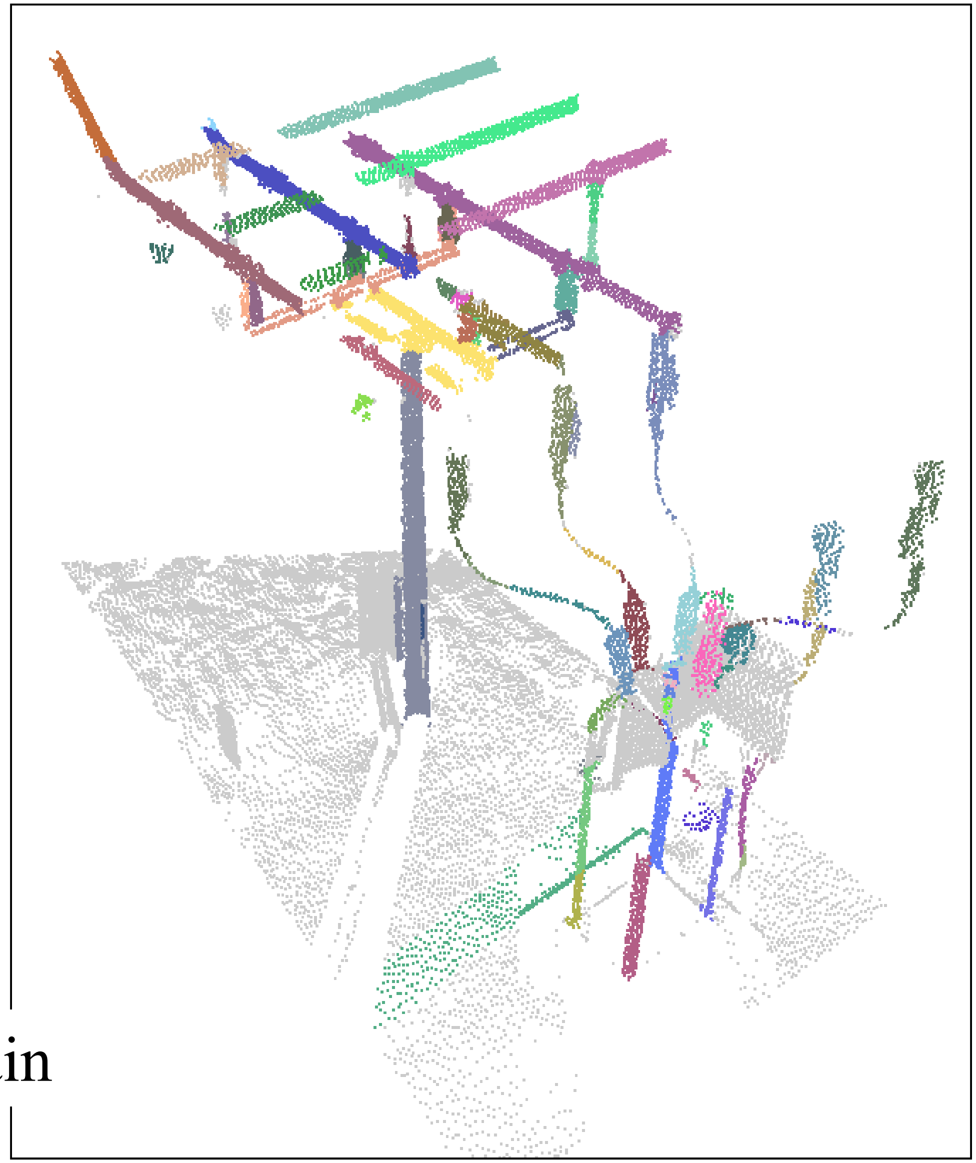


Original laser dataset



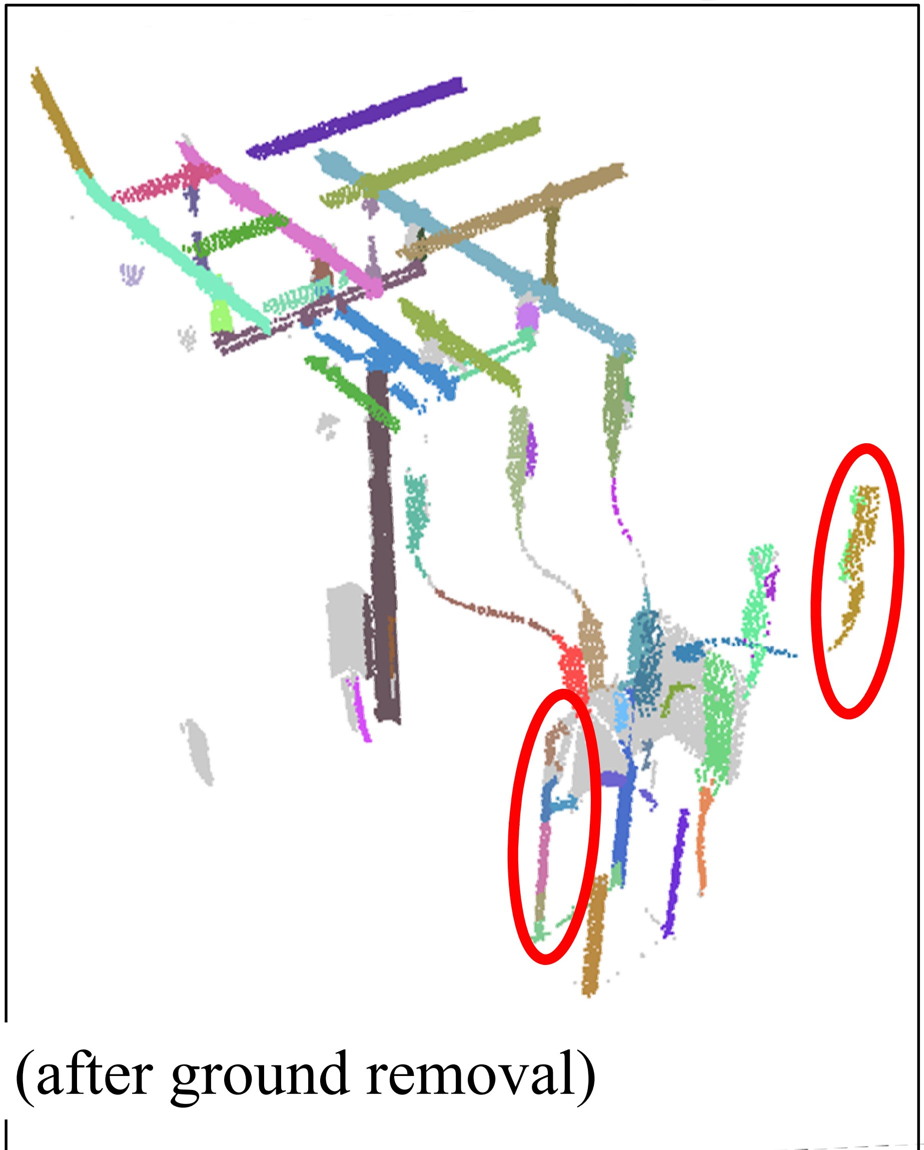
Eigen-detected linear/cylindrical features (red points)

Linear Features Segmentation Results (1)



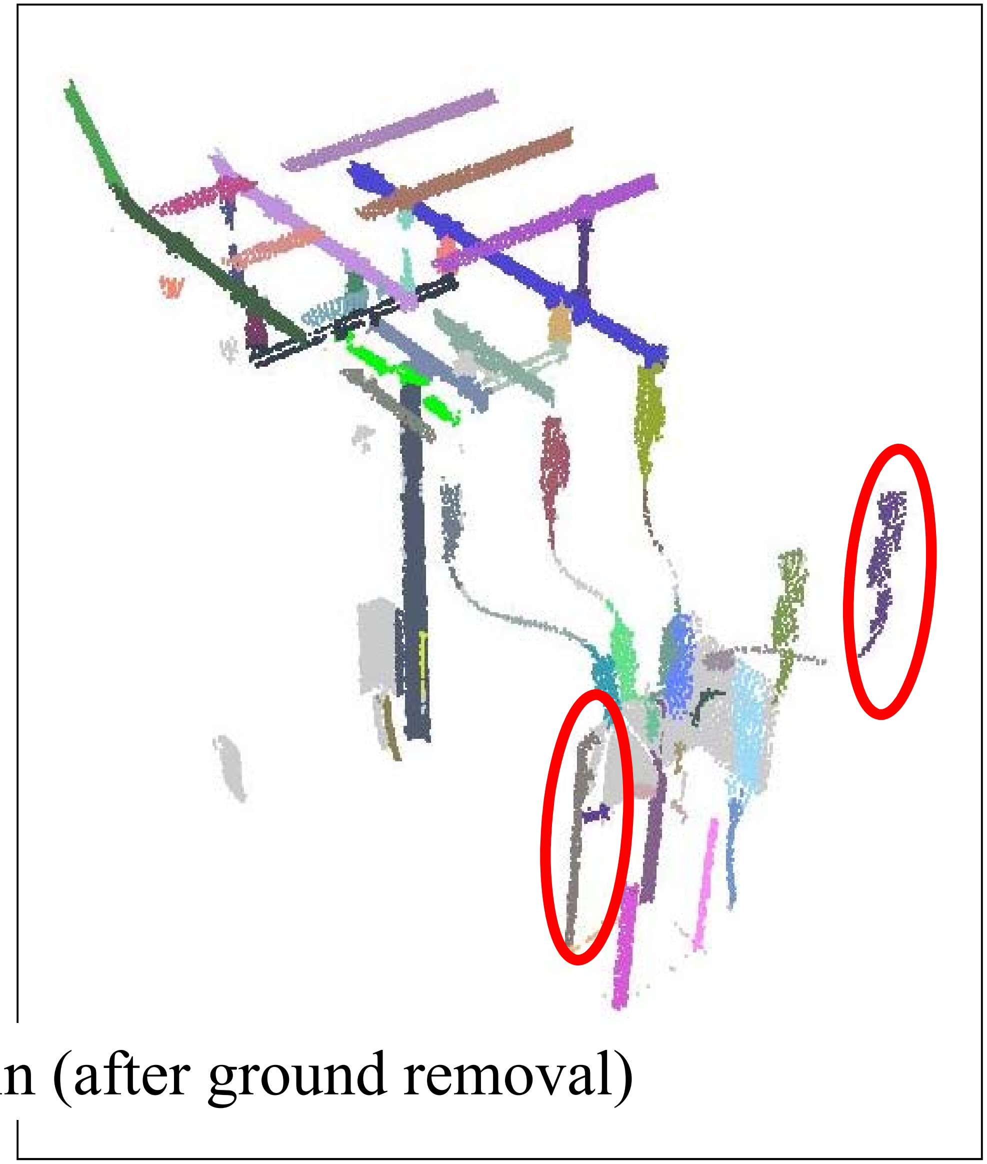
Spatial Domain

Linear Features Segmentation Results (1)



Spatial Domain (after ground removal)

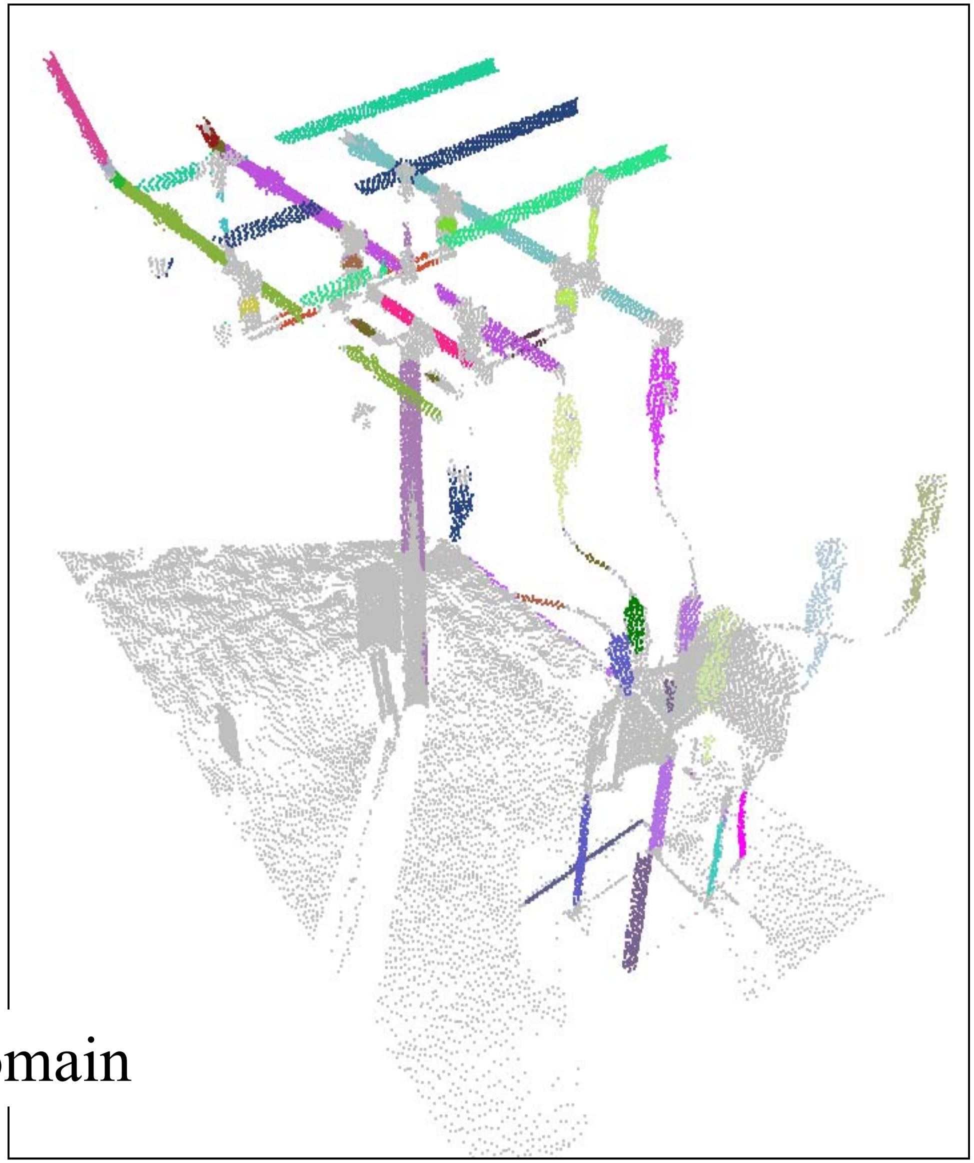
Linear Features Segmentation Results (1)



After QC

Spatial Domain (after ground removal)

Linear Features Segmentation Results (1)



After QC

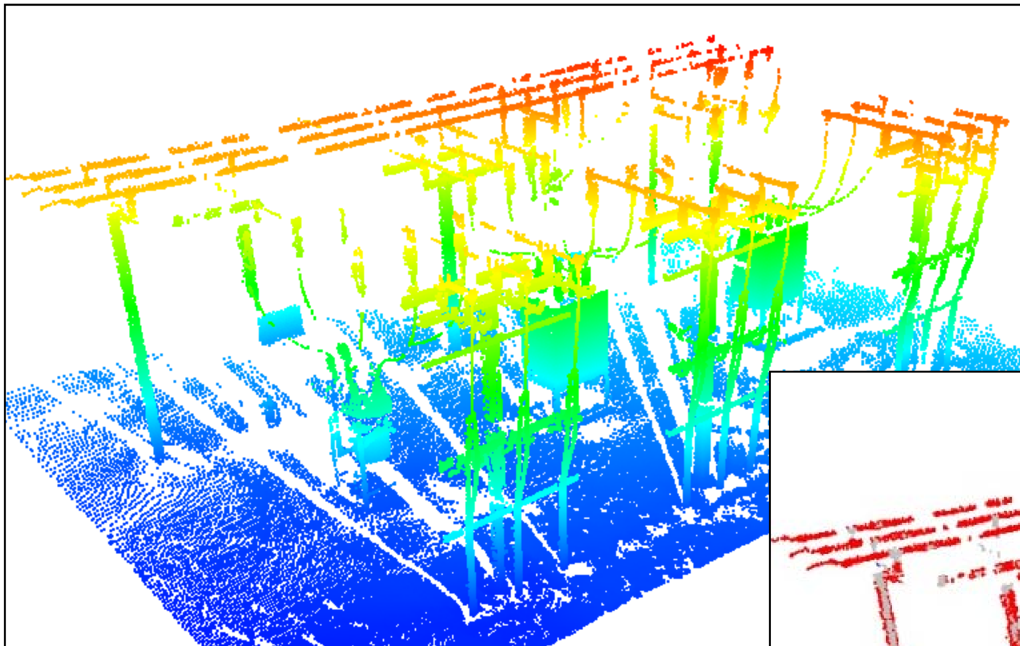
Parameter Domain

Linear Features Segmentation Results (1)

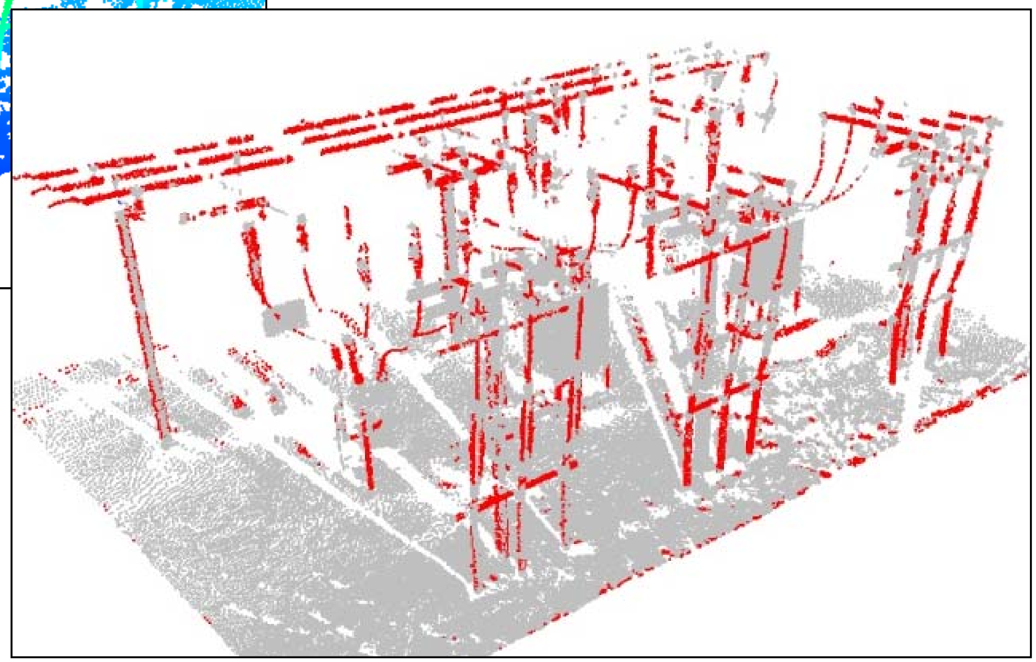
Comparative analysis of parameter-domain and spatial-domain linear/cylindrical features segmentation results

Quality control measures	Parameter-domain segmentation results	Spatial-domain segmentation results
Non-segmented linear points	14%	3%
Misclassified rough points	0%	0%
Over-segmentation	7%	12%
Under-segmentation	2%	4%

Linear Features Segmentation Results (1)

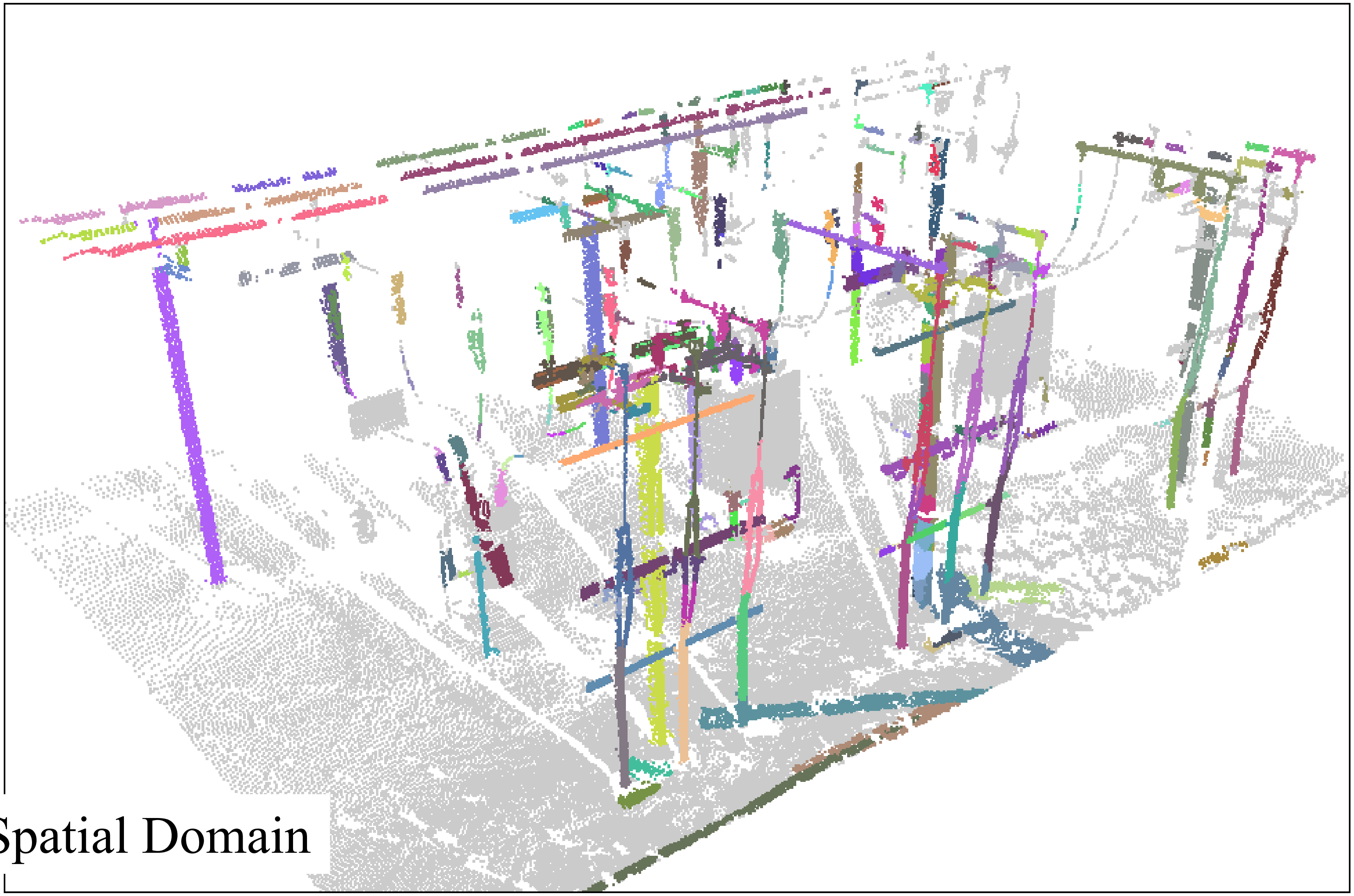


Original laser dataset



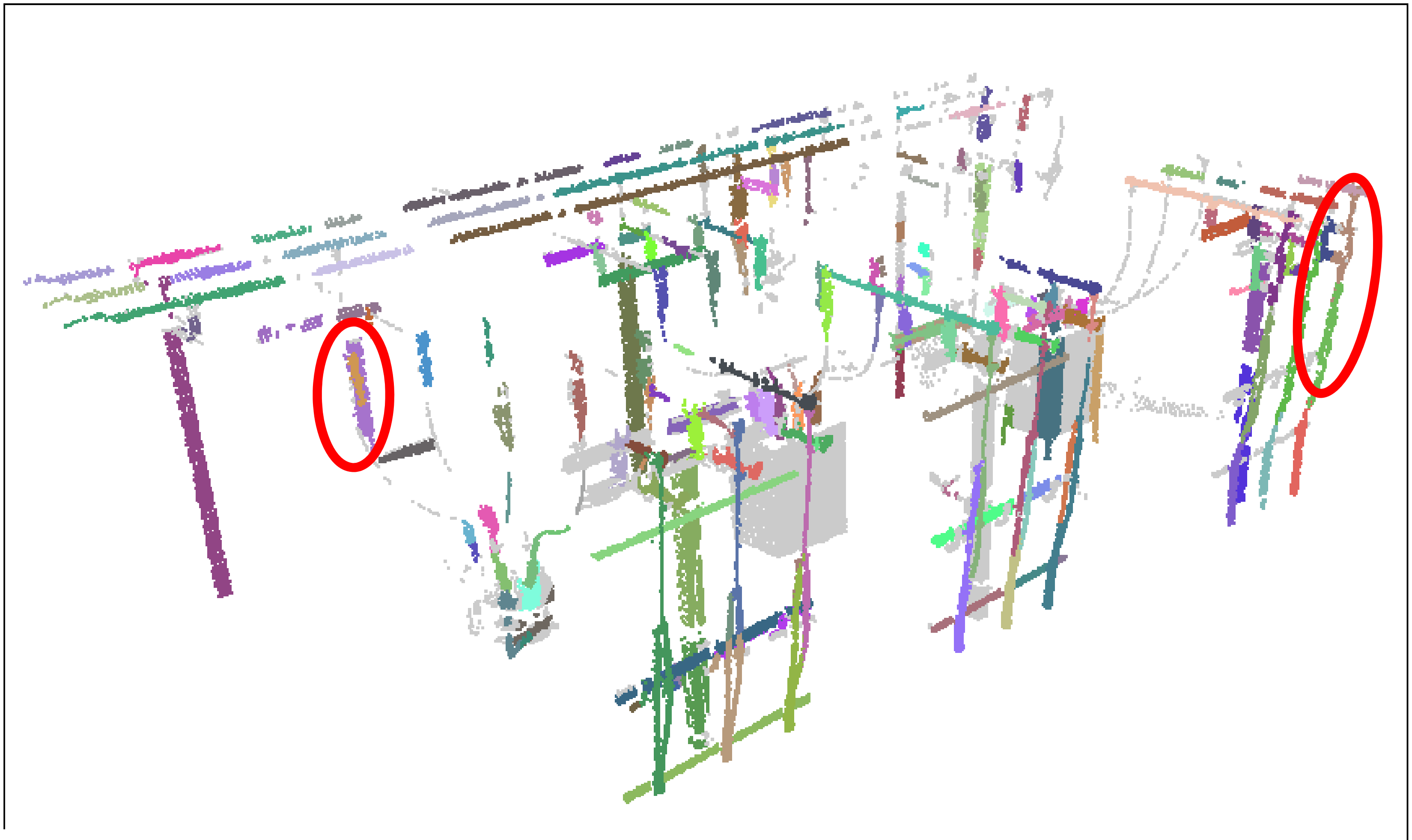
Eigen-detected linear/cylindrical features (red points)

Linear Features Segmentation Results (1)



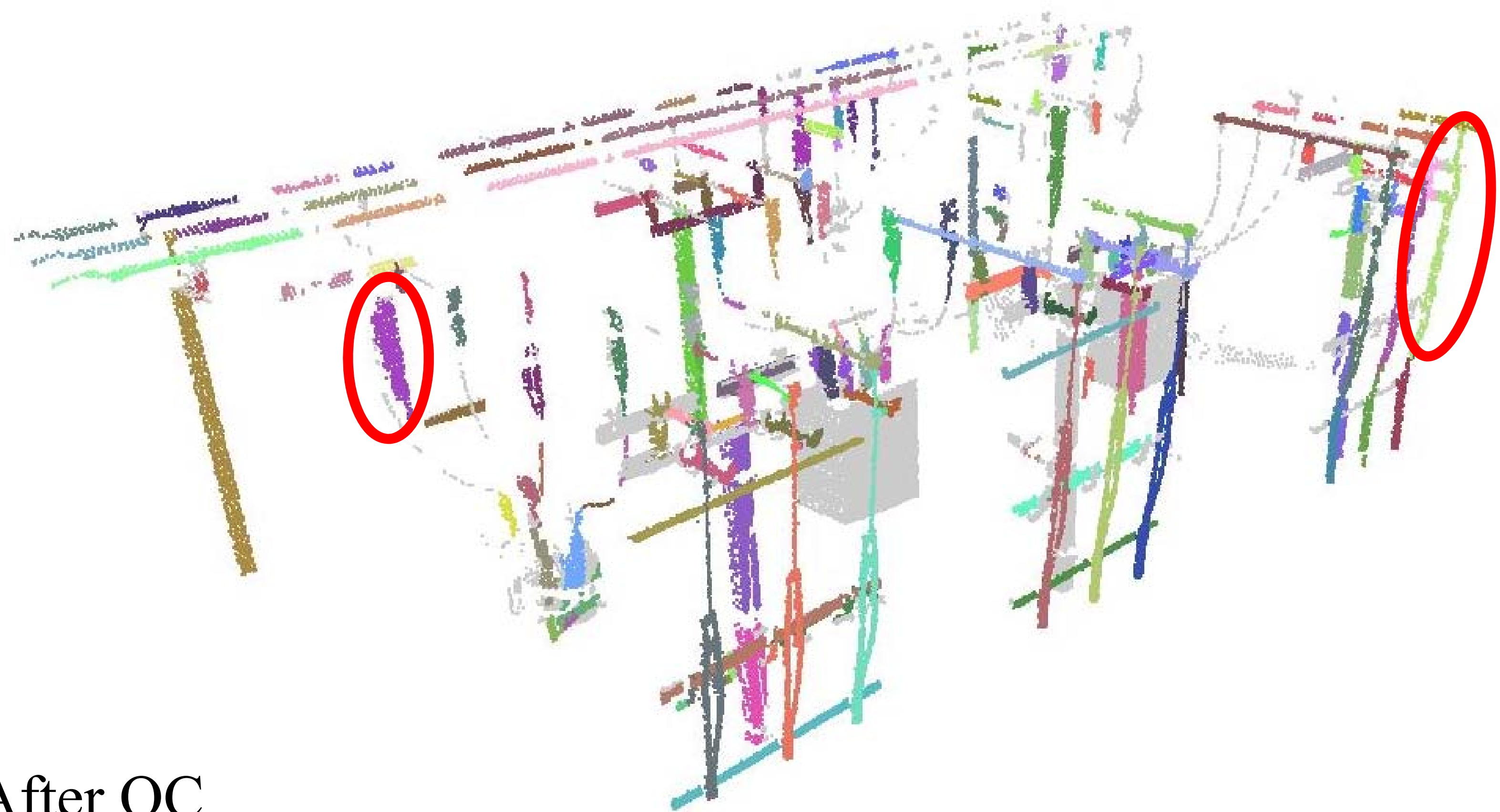
Spatial Domain

Linear Features Segmentation Results (1)



Spatial Domain (after ground filtering)

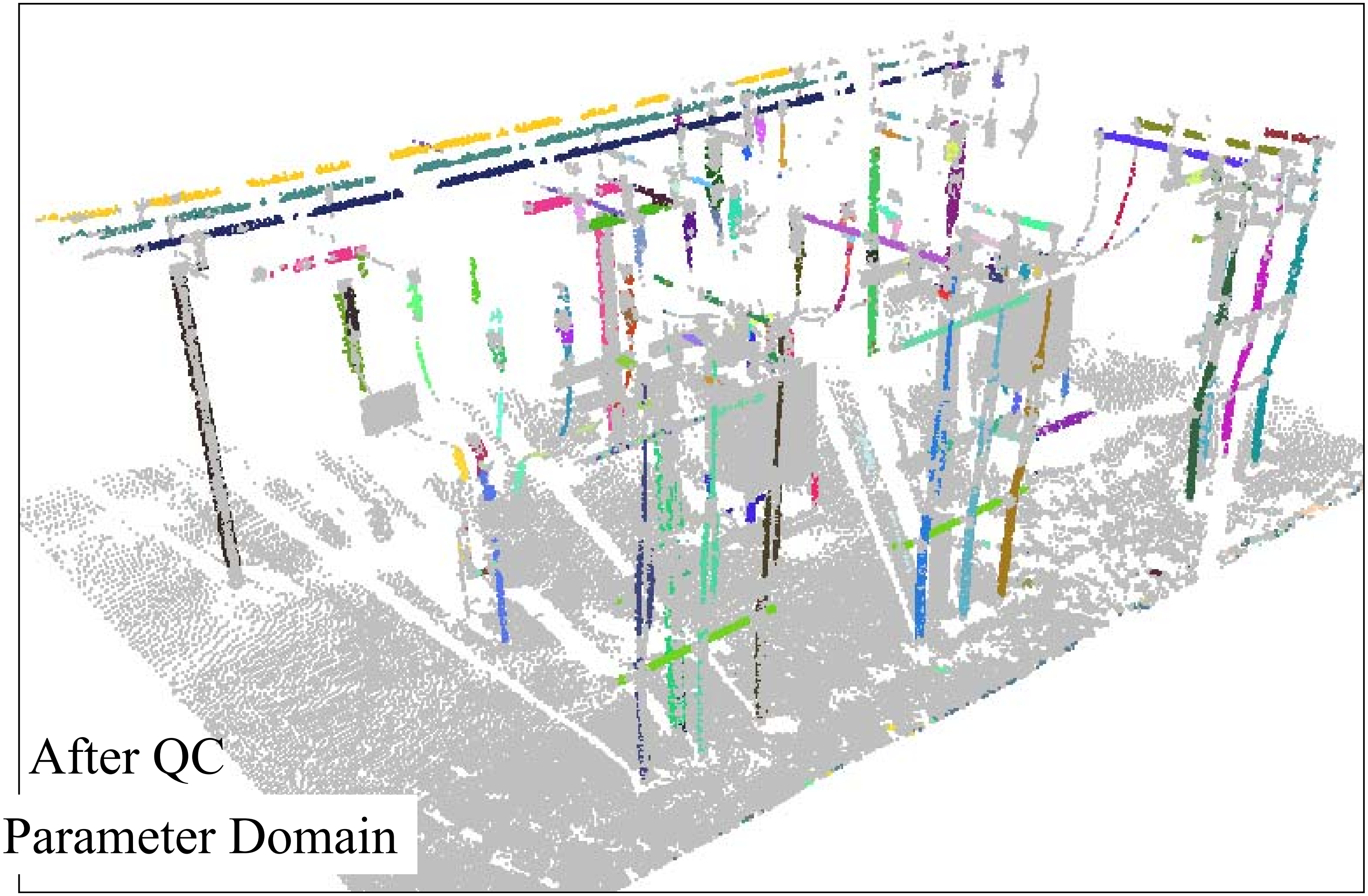
Linear Features Segmentation Results (1)



After QC

Spatial Domain (after ground filtering)

Linear Features Segmentation Results (1)



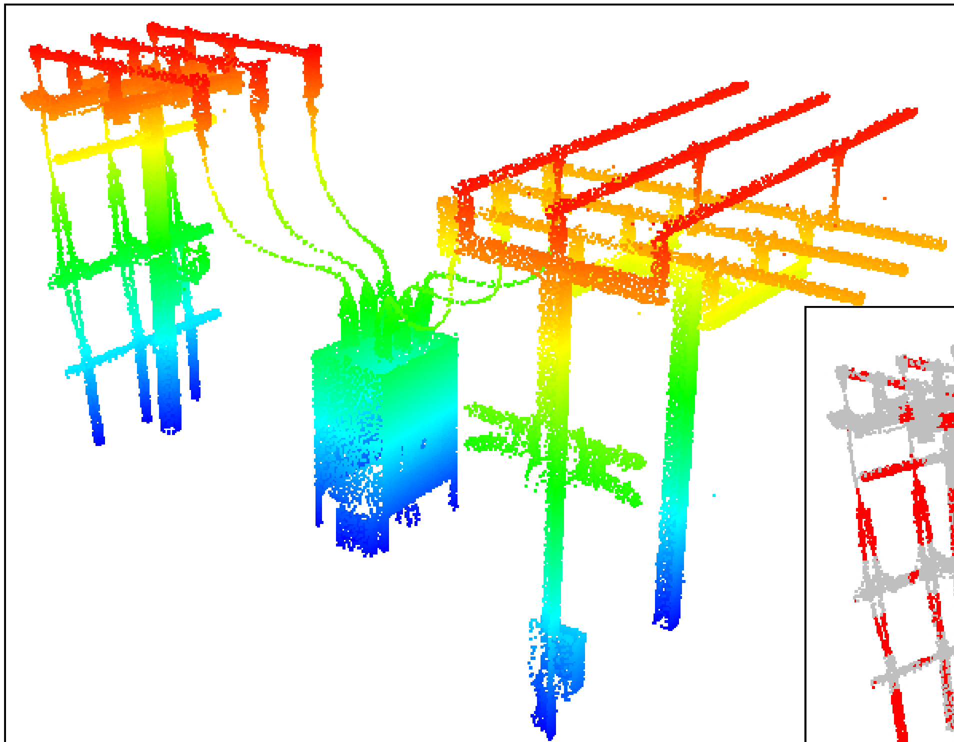
Parameter Domain

Linear Features Segmentation Results (1)

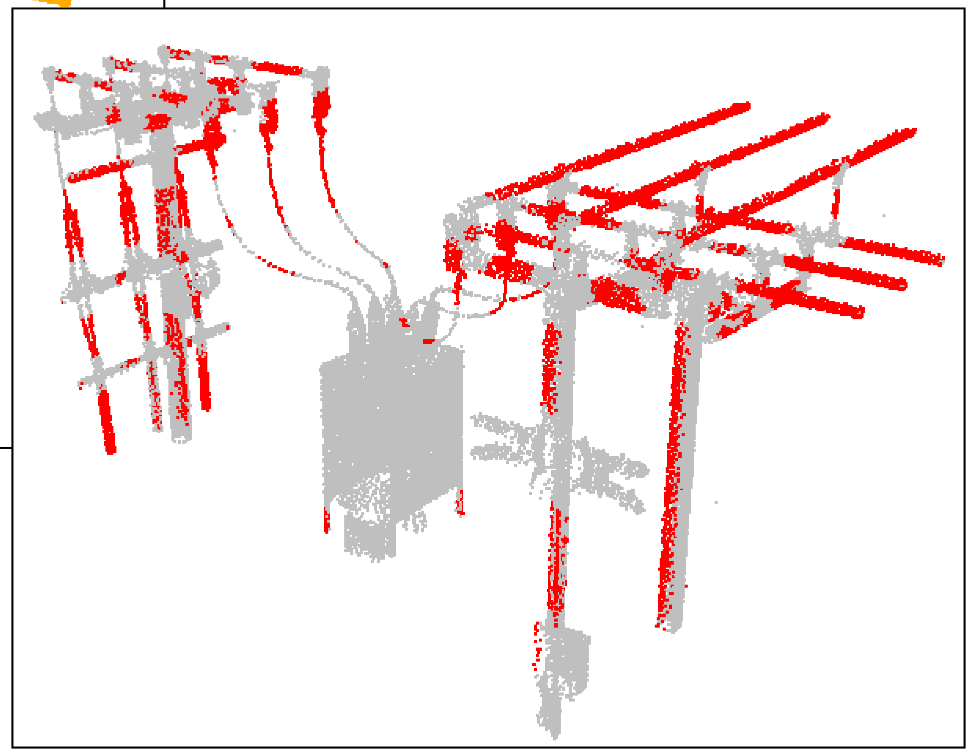
Comparative analysis of parameter-domain and spatial-domain linear/cylindrical features segmentation results

Quality control measures	Parameter-domain segmentation results	Spatial-domain segmentation results
Non-segmented linear points	7%	3%
Misclassified rough points	0%	0%
Over-segmentation	1%	9%
Under-segmentation	11%	6%

Linear Features Segmentation Results (1)

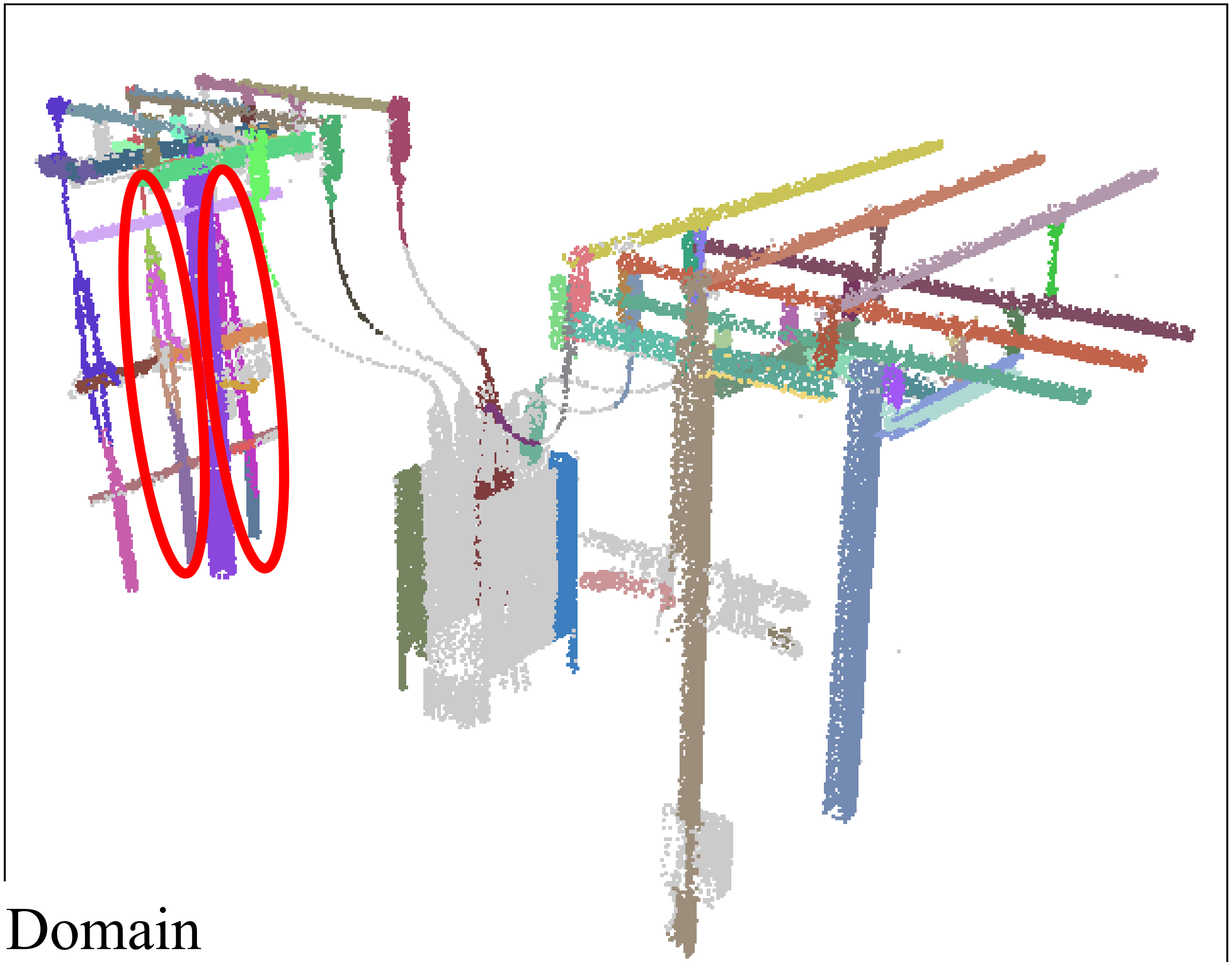


Original laser dataset



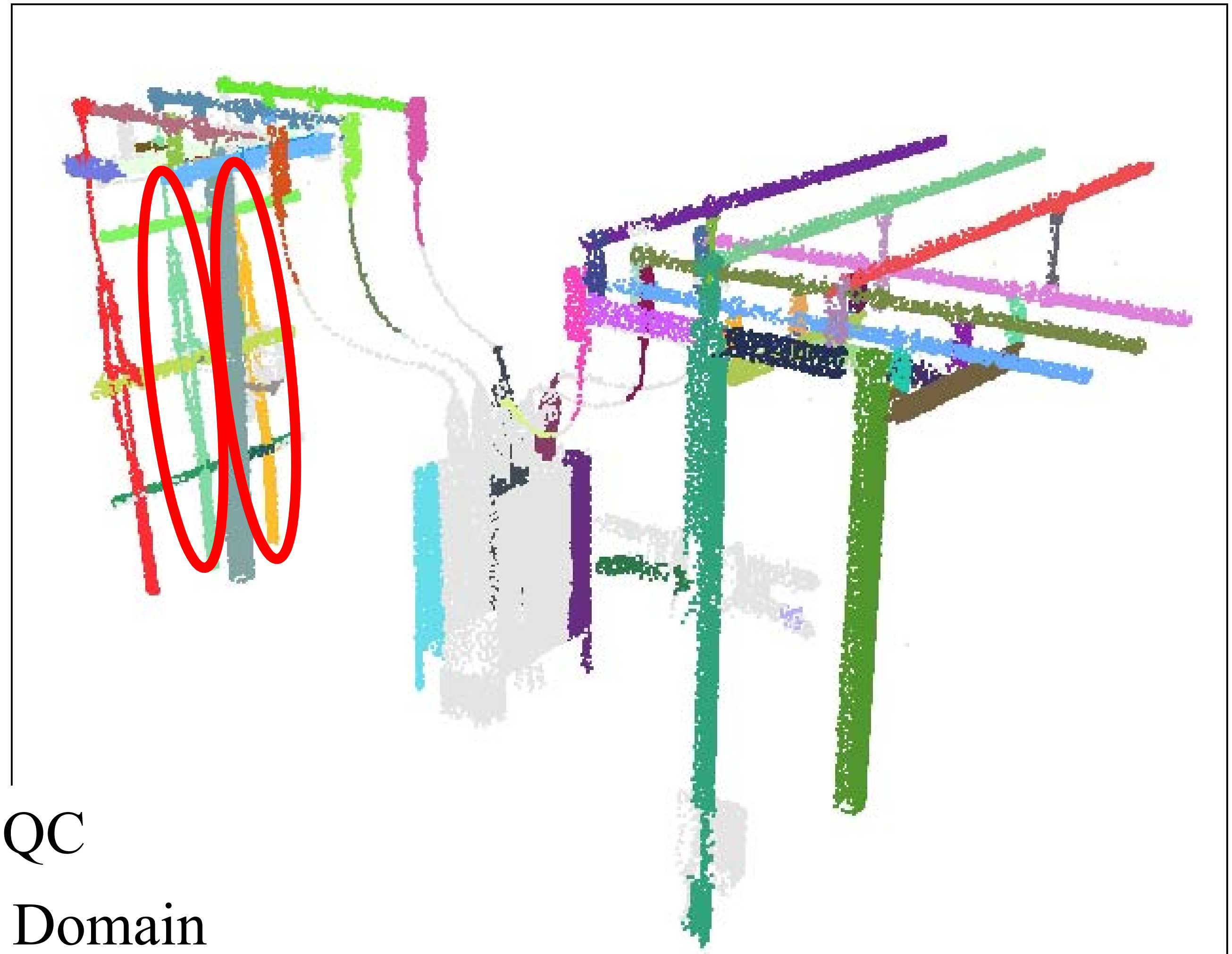
Eigen-detected linear/cylindrical features (red points)

Linear Features Segmentation Results (1)



Spatial Domain

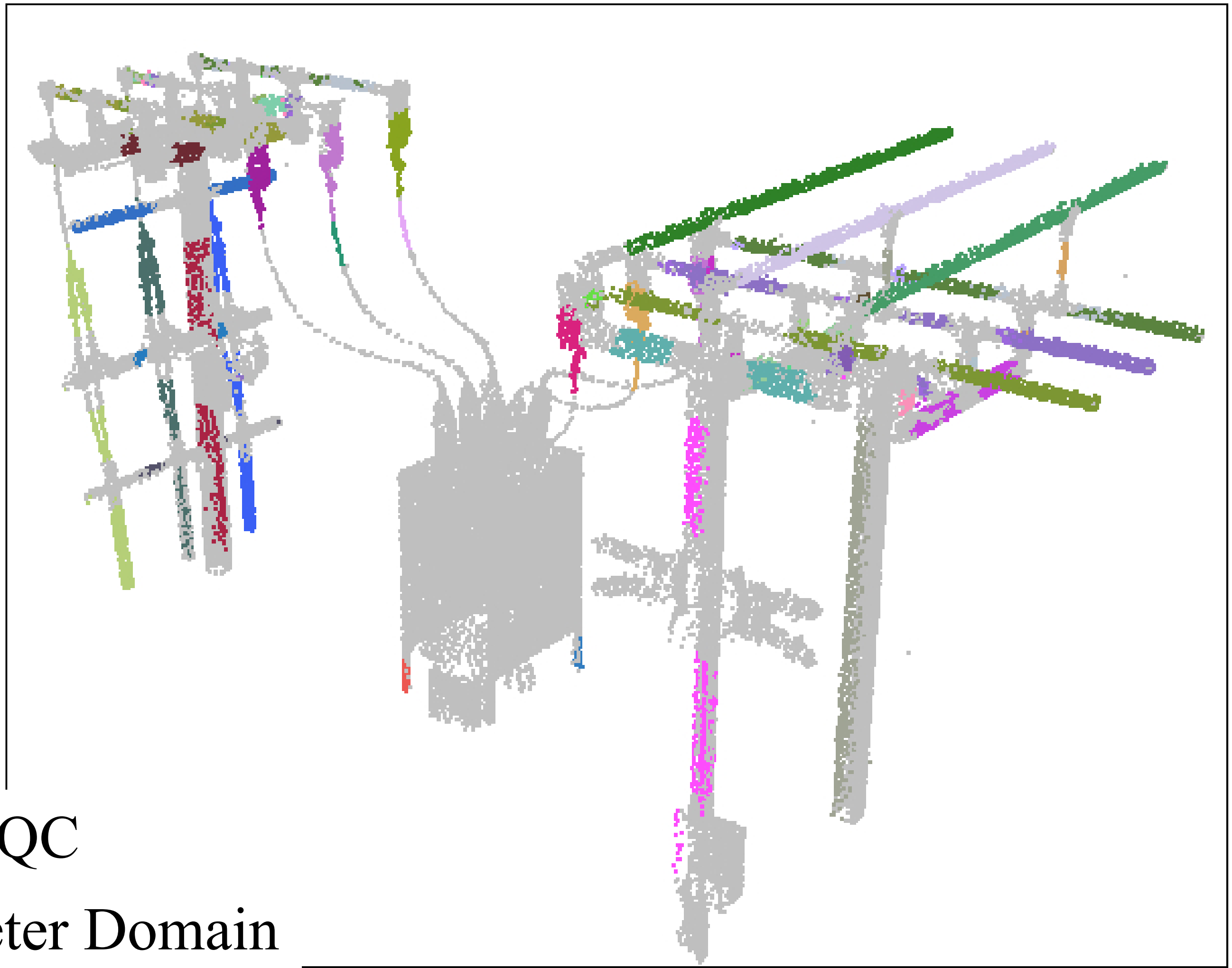
Linear Features Segmentation Results (1)



After QC

Spatial Domain

Linear Features Segmentation Results (1)



After QC

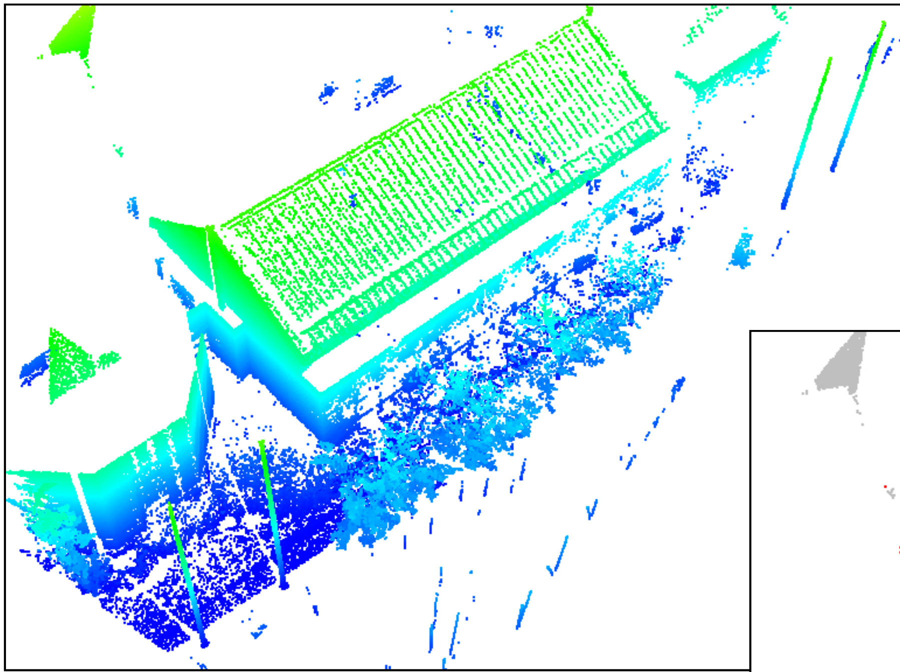
Parameter Domain

Linear Features Segmentation Results (1)

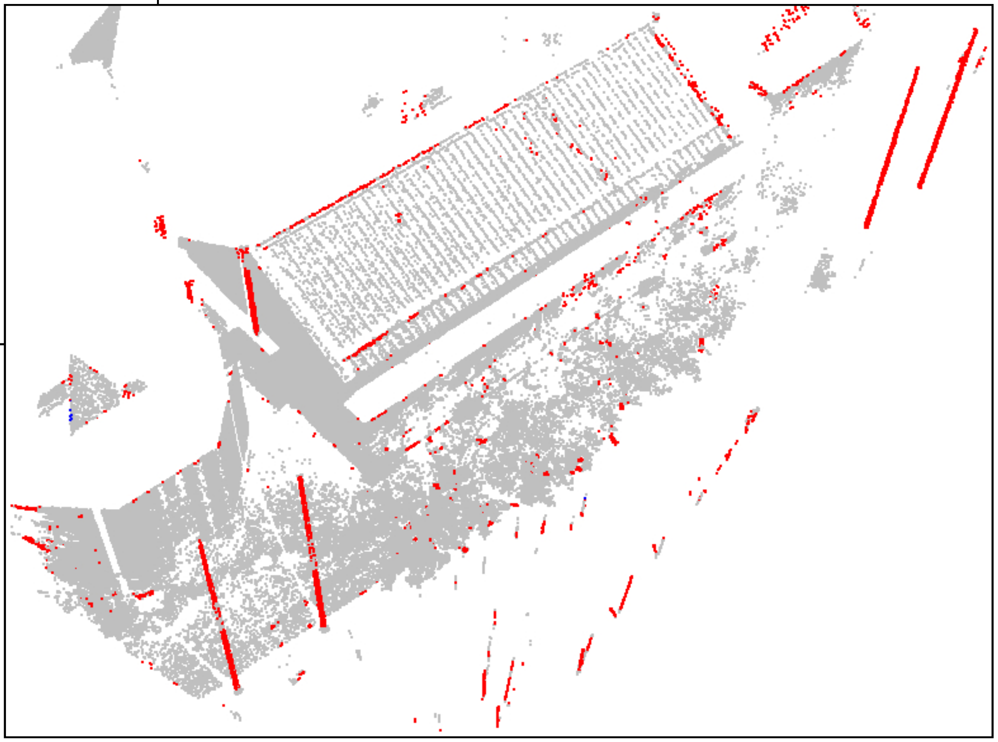
Comparative analysis of parameter-domain and spatial-domain linear/cylindrical features segmentation results

Quality control measures	Parameter-domain segmentation results	Spatial-domain segmentation results
Non-segmented linear points	4%	1%
Misclassified rough points	0%	0%
Over-segmentation	2%	13%
Under-segmentation	3%	5%

Linear Features Segmentation Results (2)

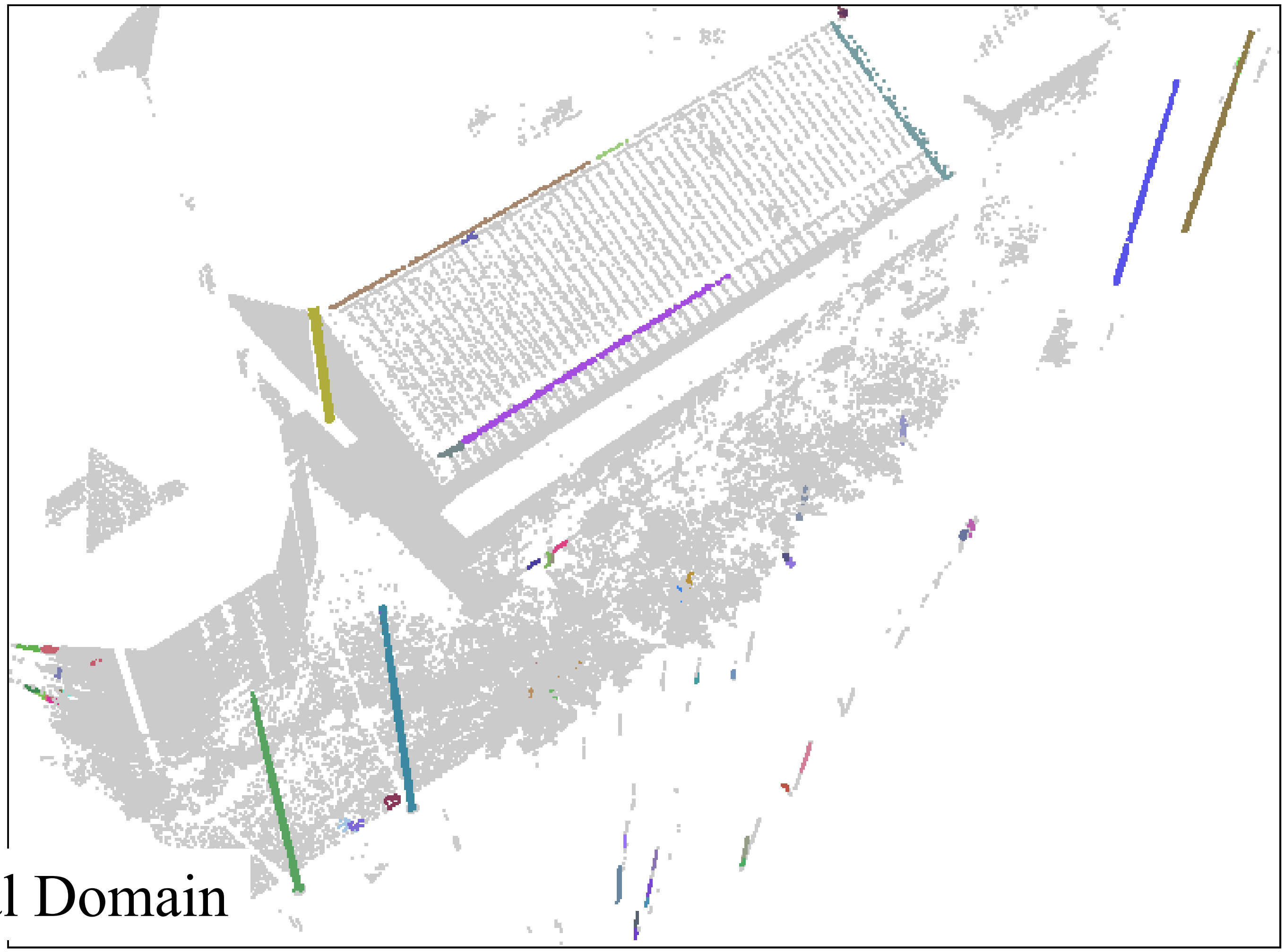


Original laser dataset



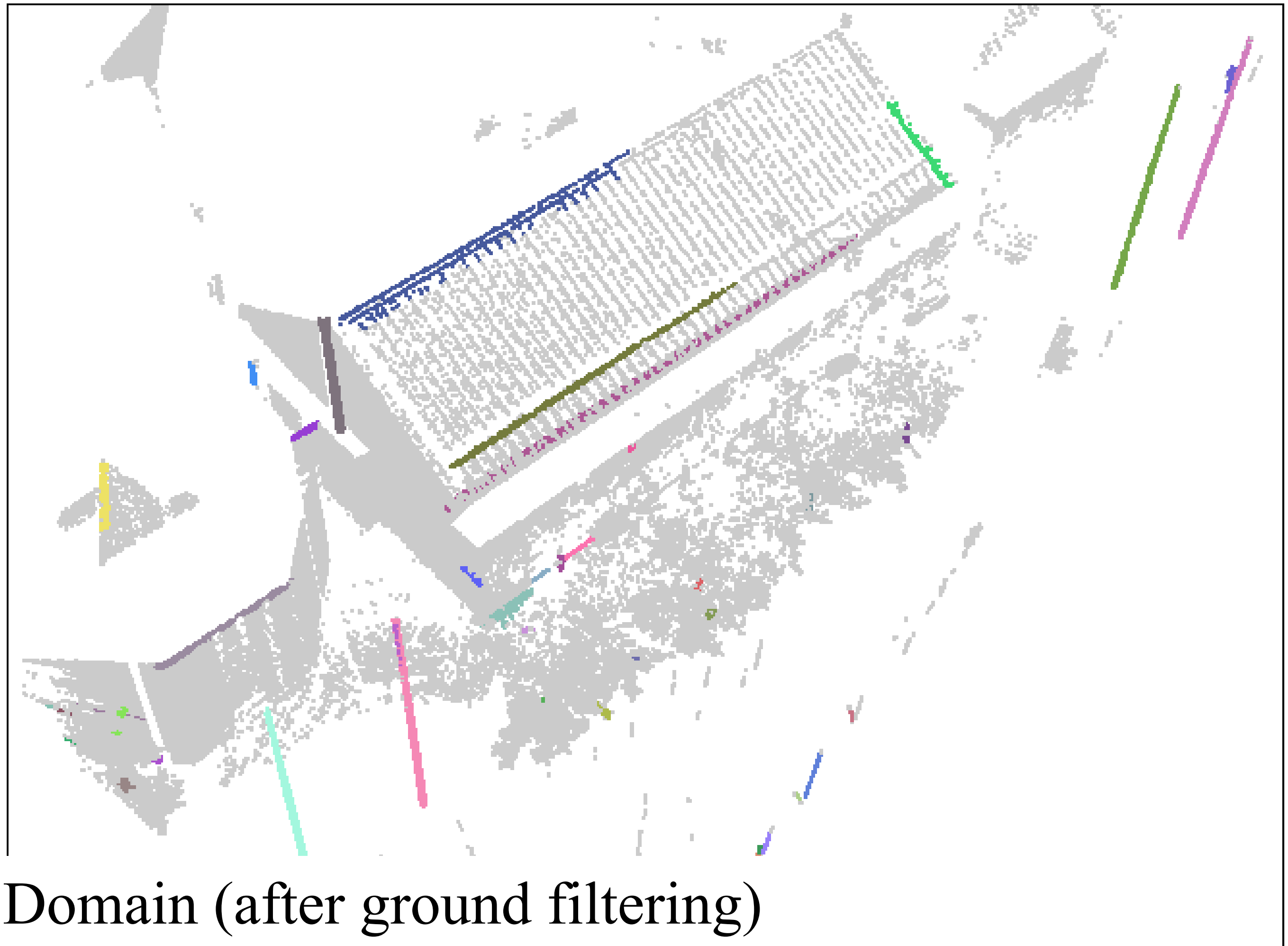
Eigen-detected linear/cylindrical features (red points)

Linear Features Segmentation Results (2)



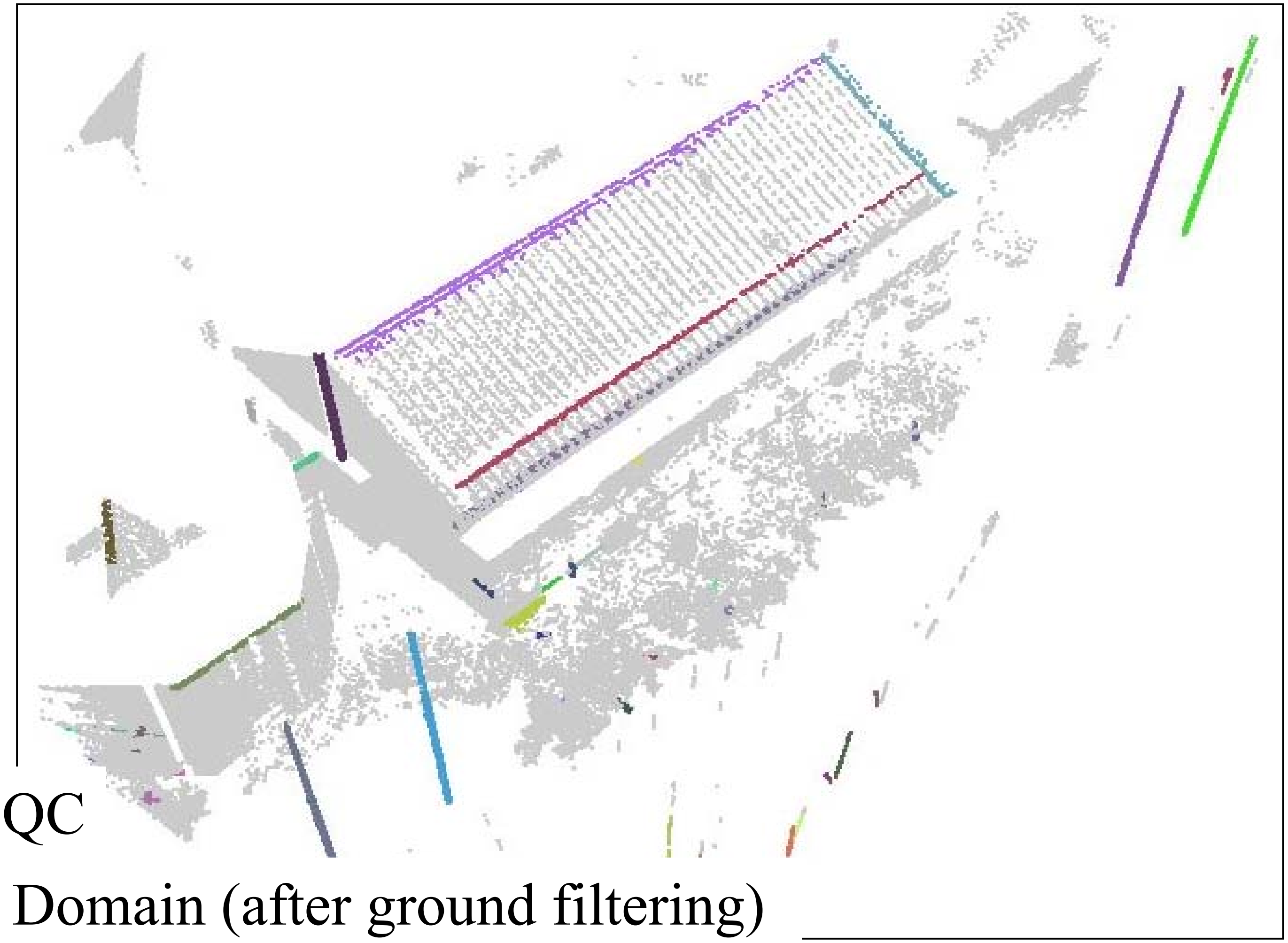
Spatial Domain

Linear Features Segmentation Results (2)



Spatial Domain (after ground filtering)

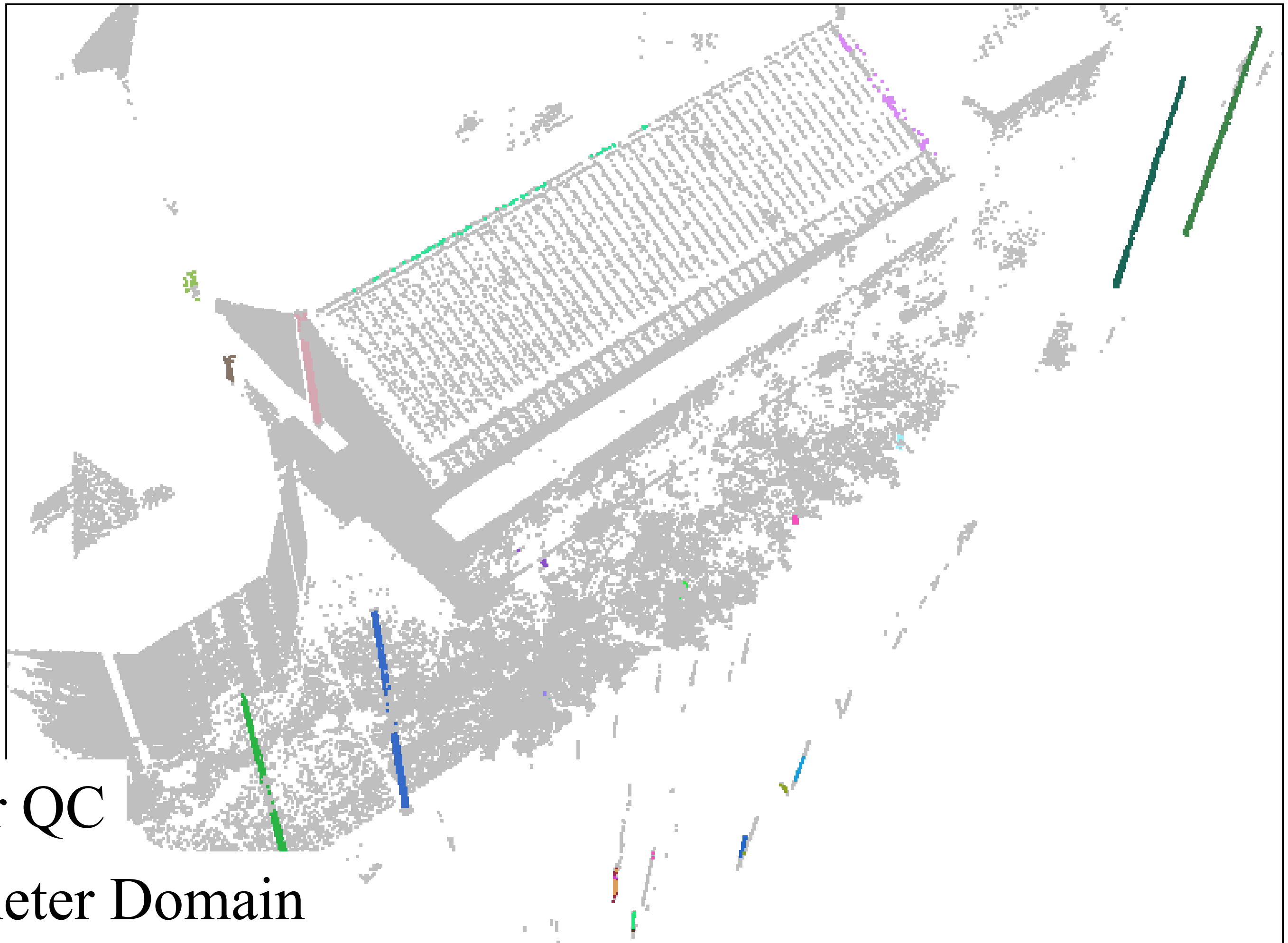
Linear Features Segmentation Results (2)



After QC

Spatial Domain (after ground filtering)

Linear Features Segmentation Results (2)



After QC

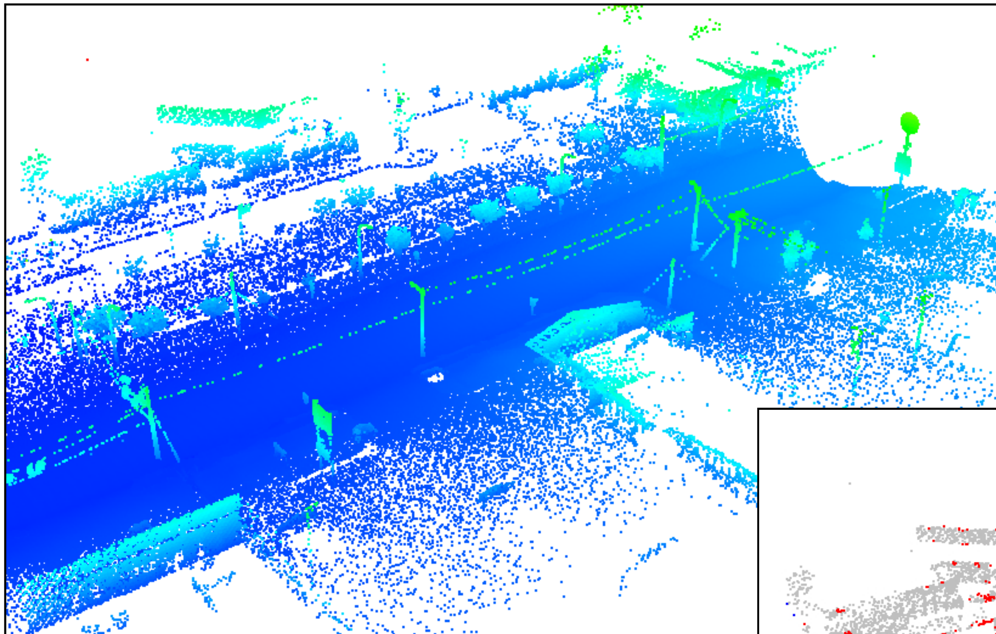
Parameter Domain

Linear Features Segmentation Results (2)

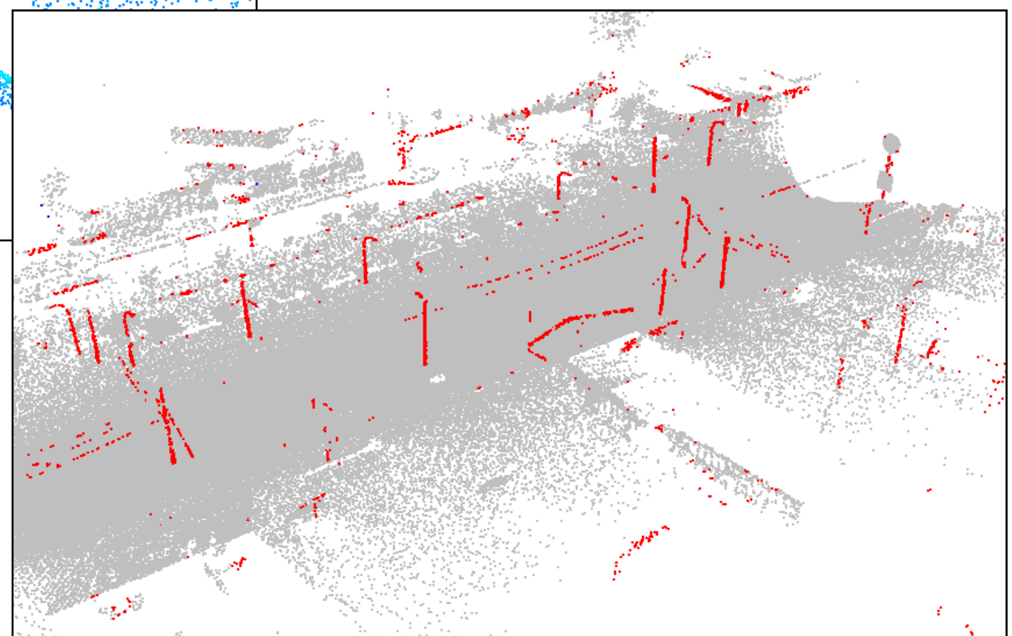
Comparative analysis of parameter-domain and spatial-domain linear/cylindrical features segmentation results

Quality control measures	Parameter-domain segmentation results	Spatial-domain segmentation results
Non-segmented linear points	0.2%	0%
Misclassified rough points	0%	0%
Over-segmentation	7%	10%
Under-segmentation	9%	5%

Linear Features Segmentation Results (3)

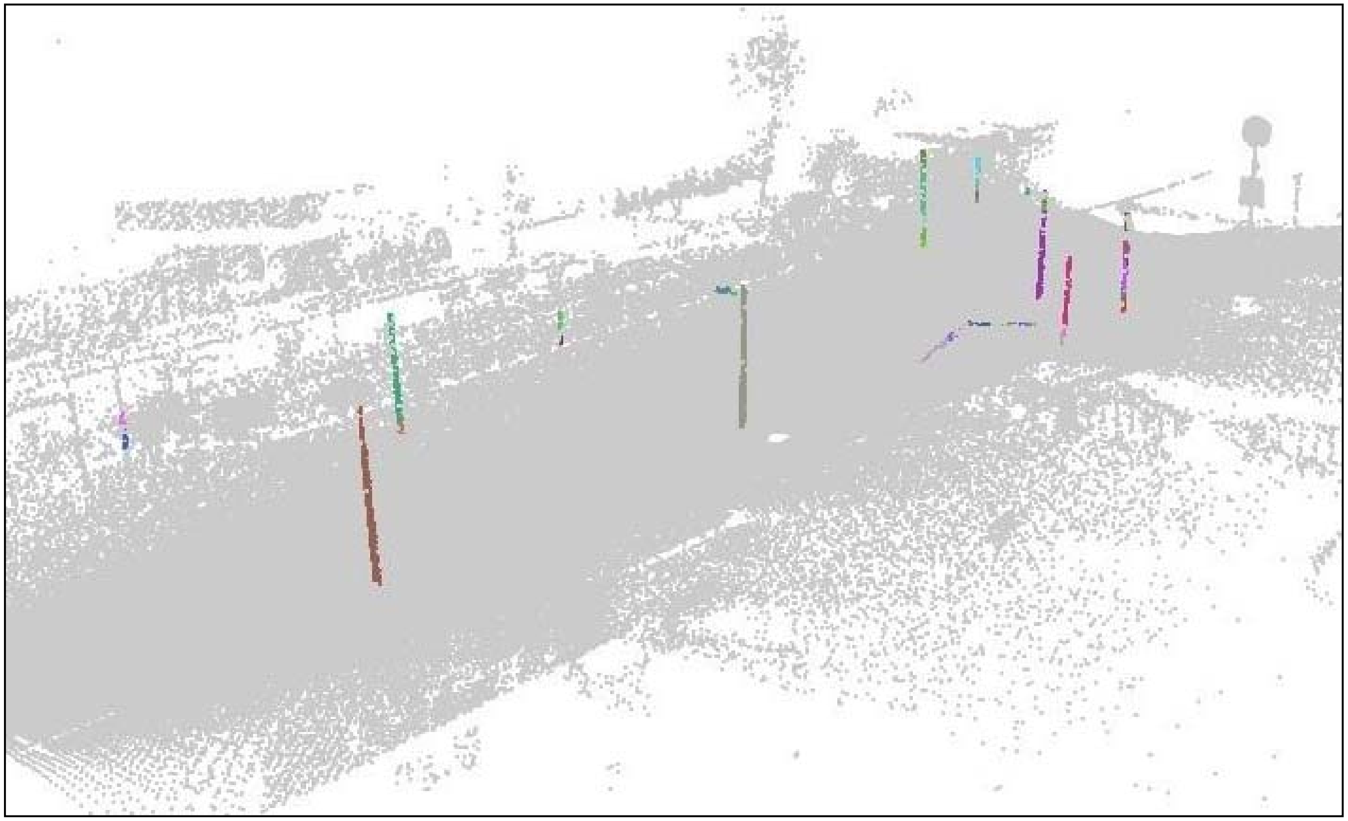


Original laser dataset



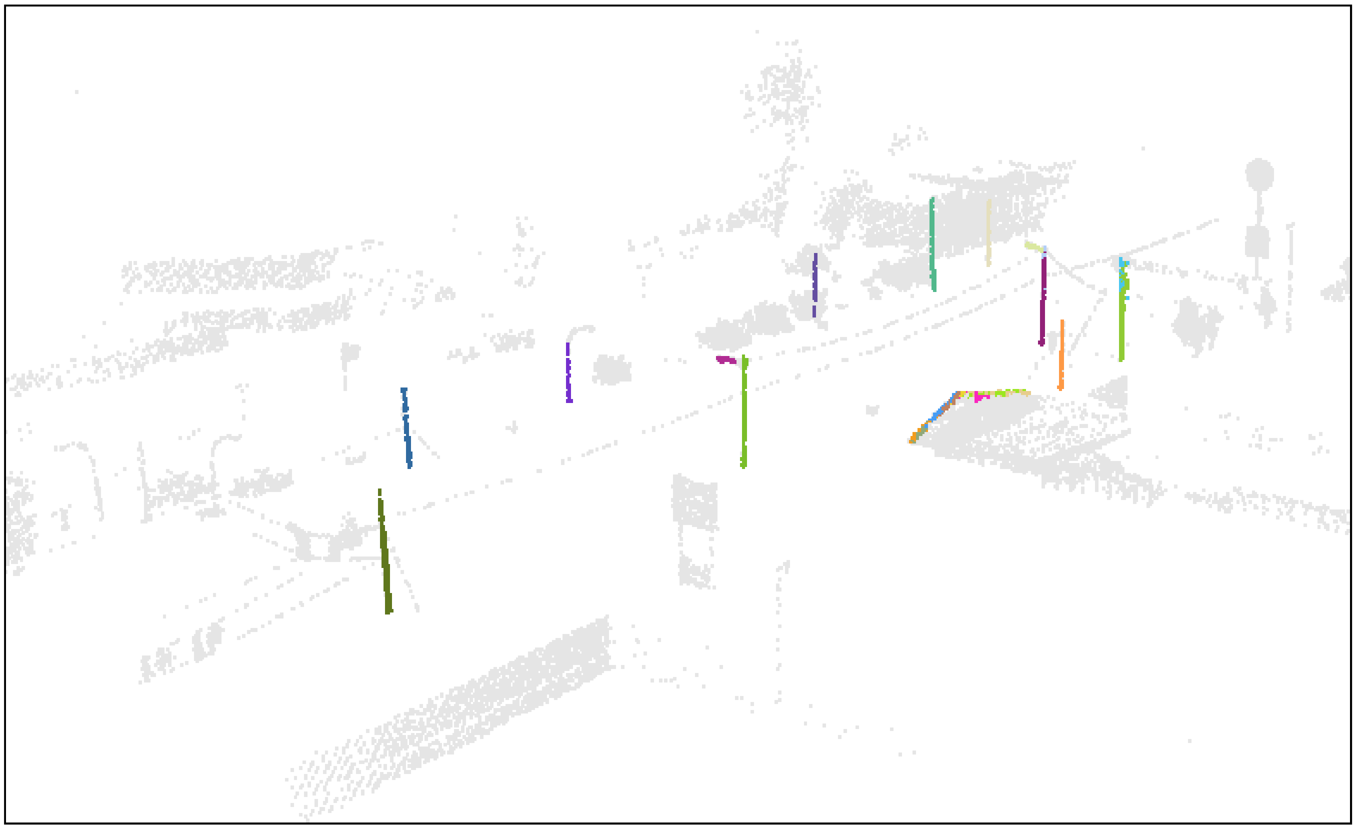
Eigen-detected linear/cylindrical features (red points)

Linear Features Segmentation Results (3)



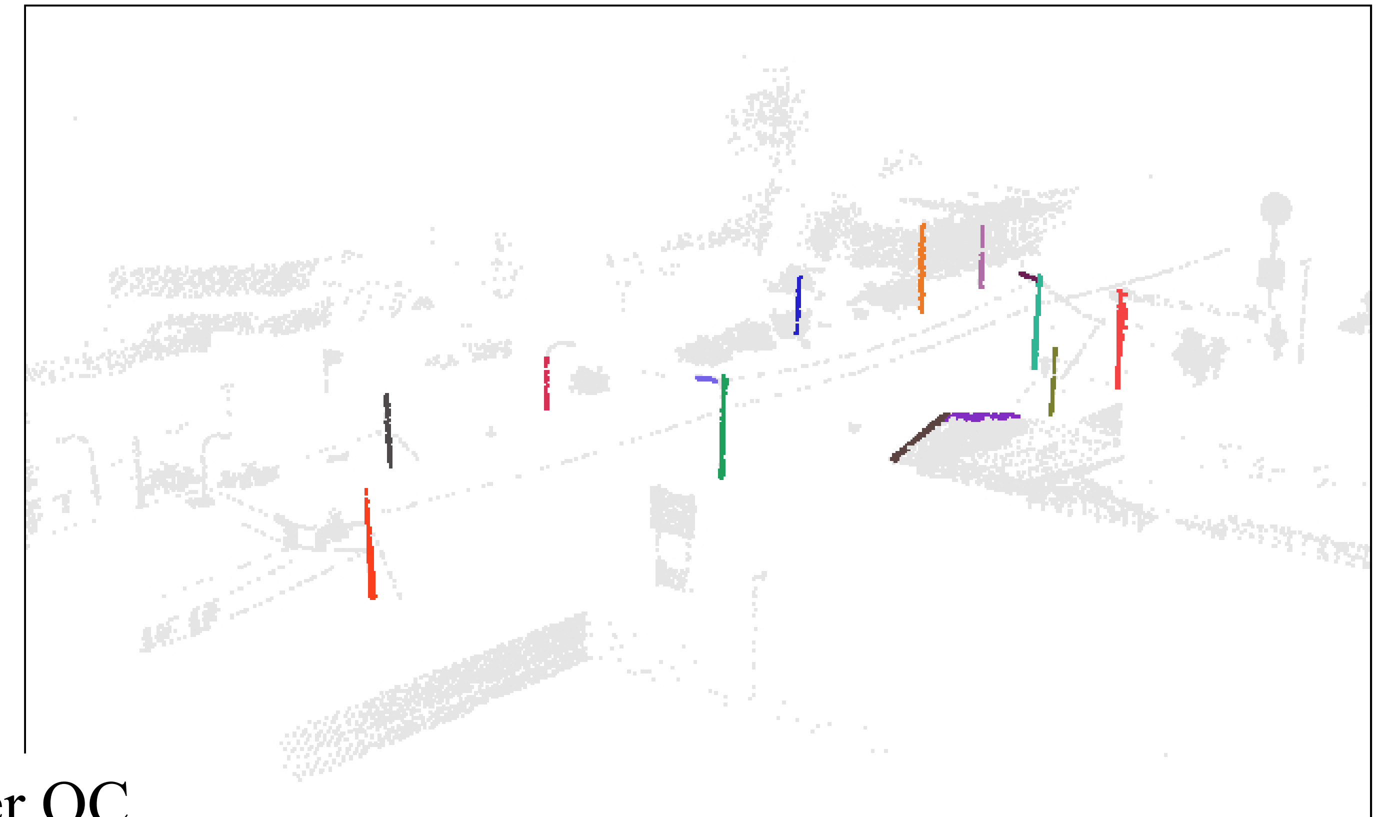
Spatial Domain

Linear Features Segmentation Results (3)



Spatial Domain (after ground filtering)

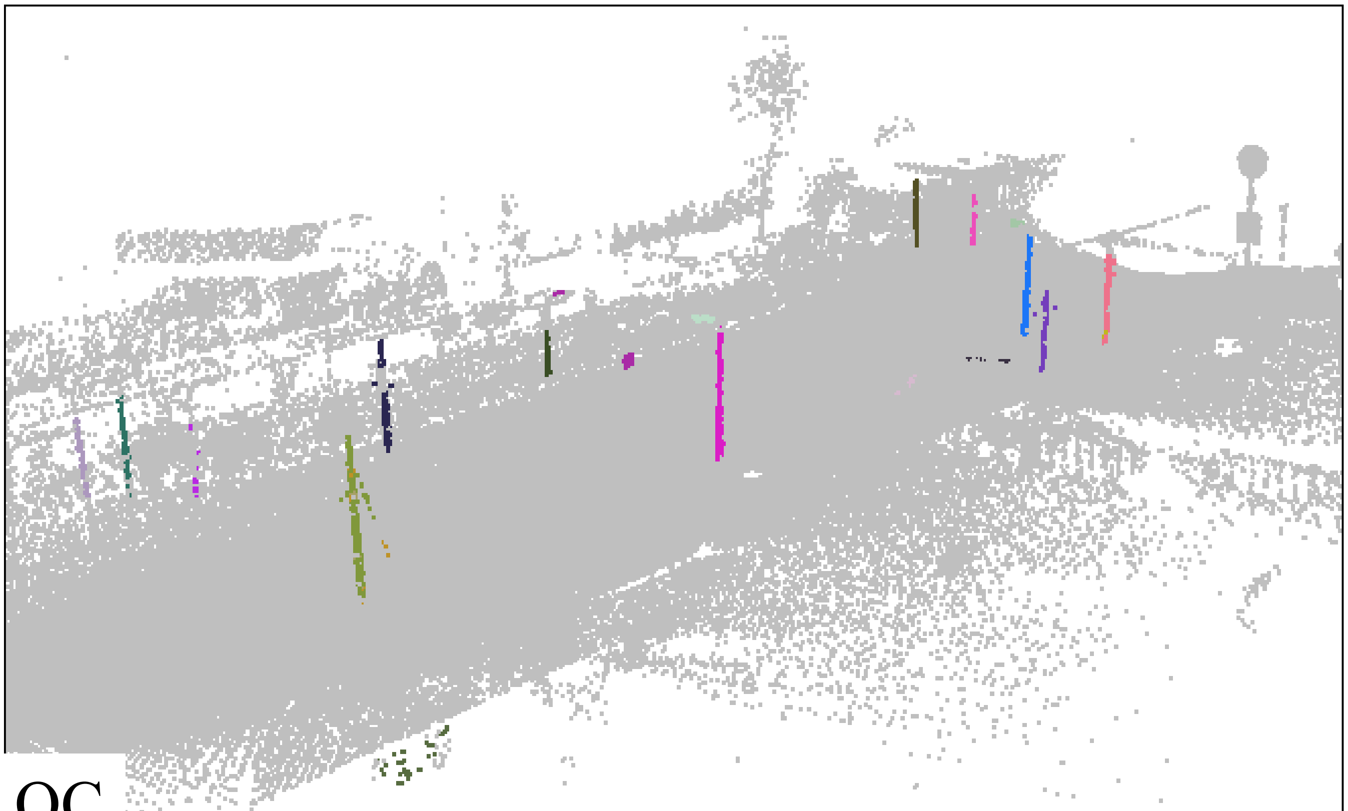
Linear Features Segmentation Results (3)



After QC

Spatial Domain (after ground filtering)

Linear Features Segmentation Results (3)



After QC

Parameter Domain

Linear Features Segmentation Results (3)

Comparative analysis of parameter-domain and spatial-domain linear/cylindrical features segmentation results

Quality control measures	Parameter-domain segmentation results	Spatial-Domain segmentation results
Non-segmented linear points	0.5%	0%
Misclassified rough points	1%	0%
Over-segmentation	14%	21%
Under-segmentation	10%	7%

LiDAR Data Segmentation

Concluding Remarks

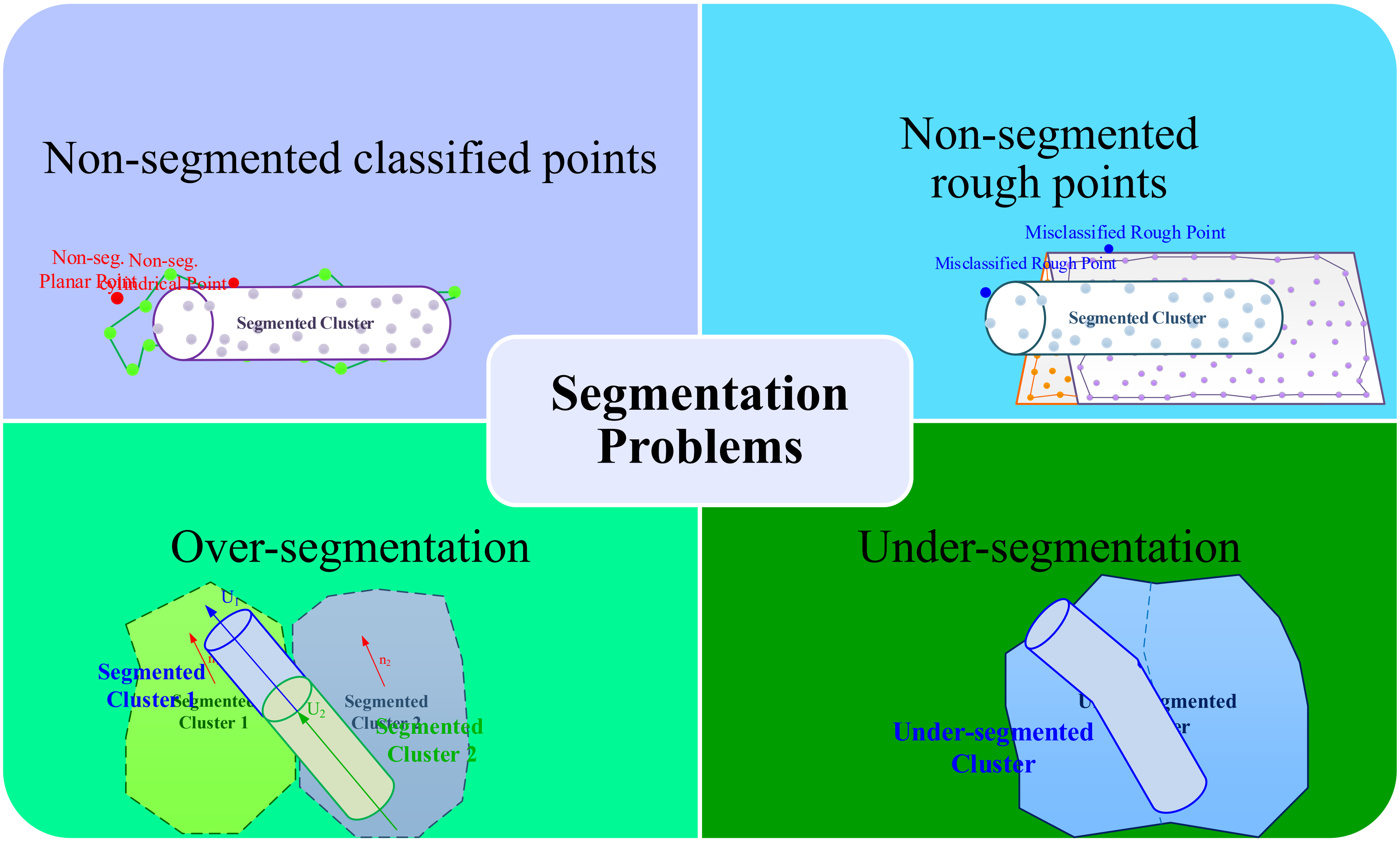
QC of LiDAR Data Segmentation

- Objective: Establish a procedure to evaluate the **quality** of the outcome from the segmentation process

Proposed quality control procedure

1. Hypothesize different scenarios/problems in the segmentation results
2. Develop procedures for detecting/identifying these problems
3. Suggest possible actions to remedy these problems

QC of LiDAR Data Segmentation



Concluding Remarks

- LiDAR systems on different platforms will deliver point clouds with varying characteristics.
- We need to redefine the local point density to suit the needs of LiDAR data processing activities (e.g., segmentation and feature extraction).
- This work provided alternatives for the estimation of the local point density for planar and linear feature extraction procedures.
- The work also presented different techniques for the segmentation/extraction of planar and linear features as well as the QC of the outcome from this process.

Current & Future Work

- Current work is focusing on using the extracted features for the automated registration of terrestrial laser scans.
- We are also working on comparative analysis of laser scanning point clouds and the outcome of image-based dense matching techniques.
  - Registration of laser scanning and image data
  - Correlating the image-based spectral information with the laser-based positional information
- We are also working on automated feature extraction from collected point clouds by a terrestrial mobile laser scanning systems for the purpose of road furniture inventory.

QUESTIONS