SEMANTIC SEGMENTATION OF POINT CLOUDS WITH THE 3D MEDIAL AXIS TRANSFORM

Giulia Ceccarelli

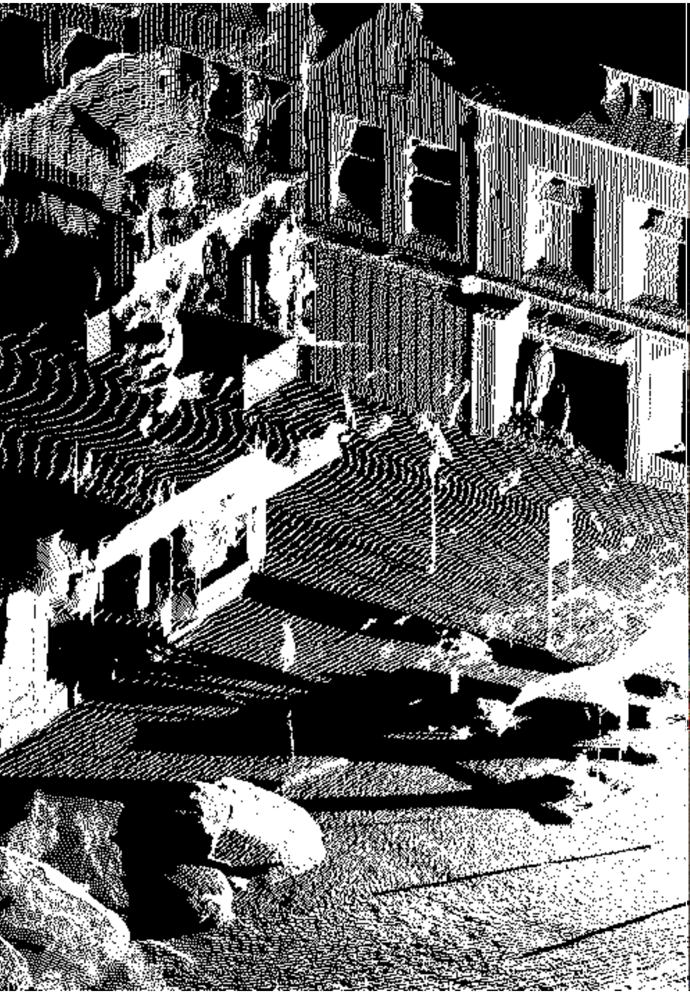
TU Delft

Ravi Peters
Weixiao Gao

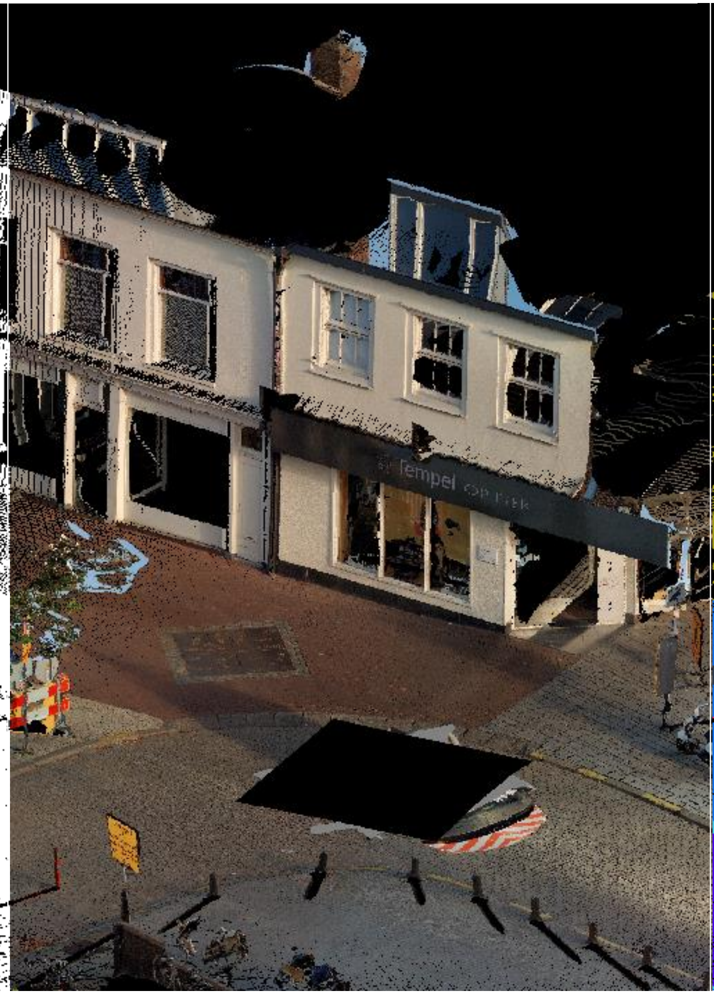
cyclomedia

Bas Boom
Arjen Swart

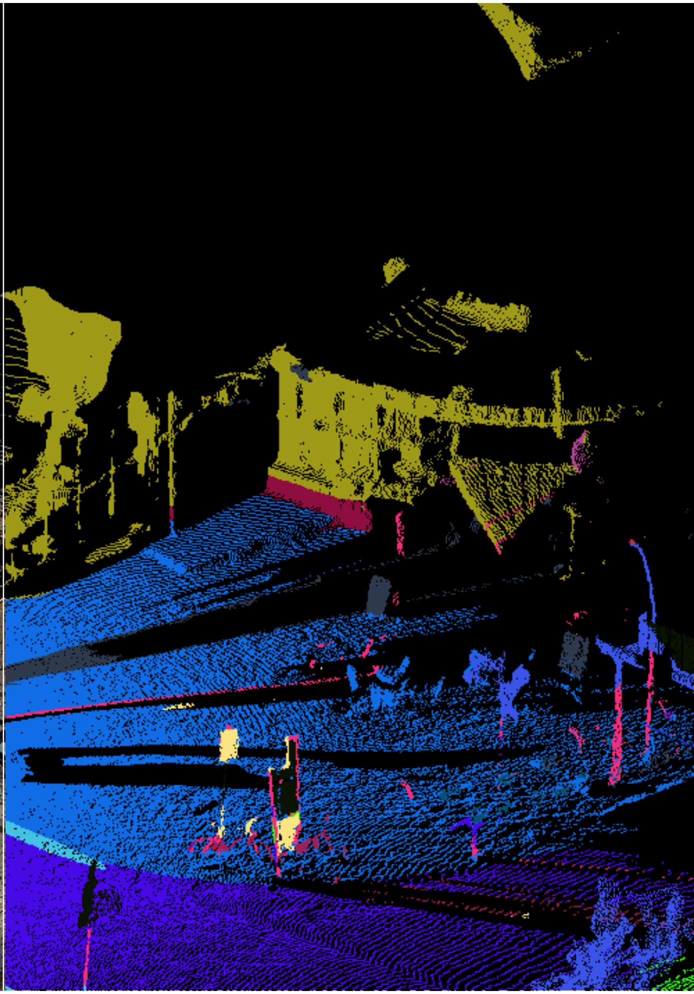
INTRODUCTION
Point clouds



Raw point cloud

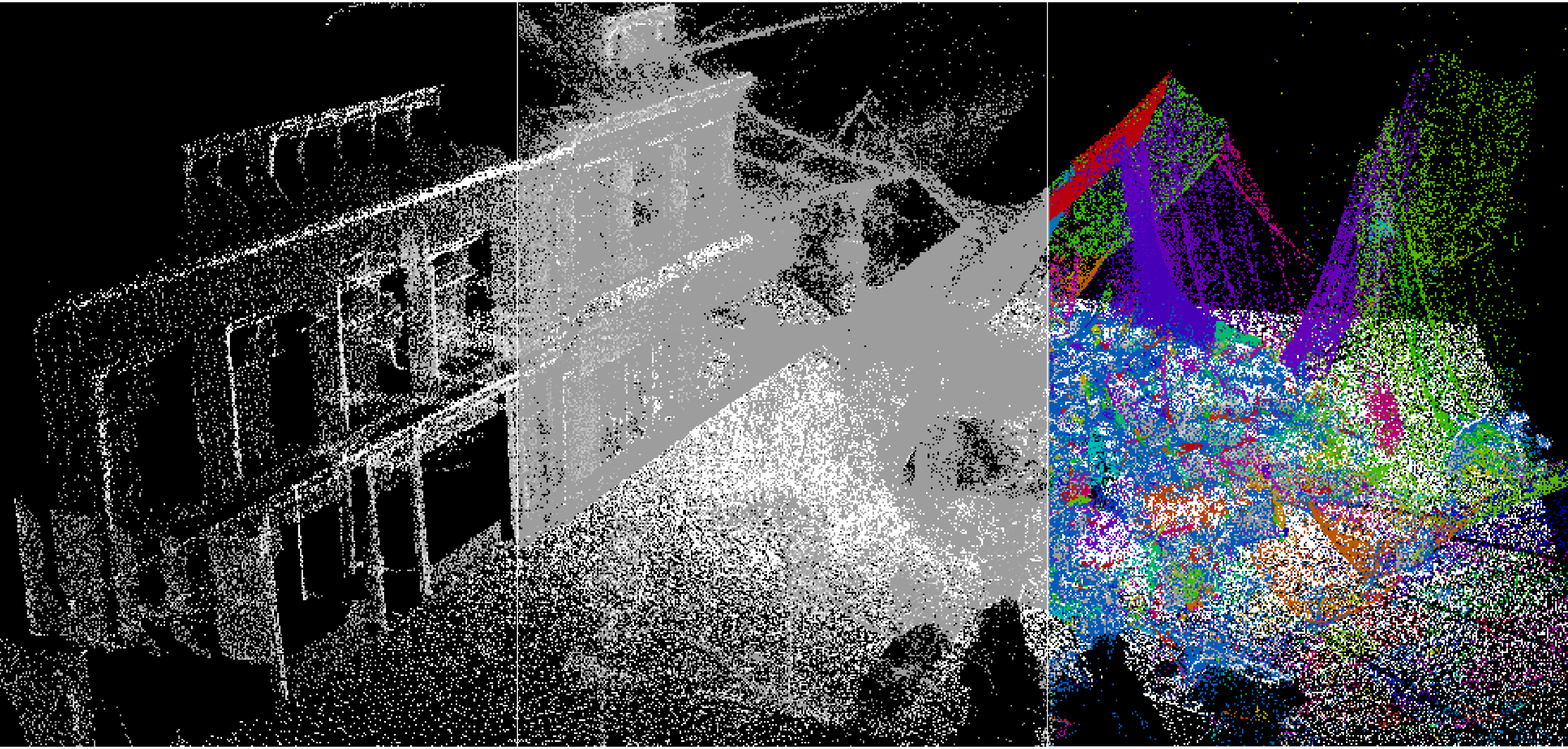


RGB point cloud



Segmented point cloud

INTRODUCTION
3D medial axis transform



Raw point cloud | Medial axis transform | Structured medial axis transform

TUDelft cyclomedia

RESEARCH QUESTIONS
& problem statement

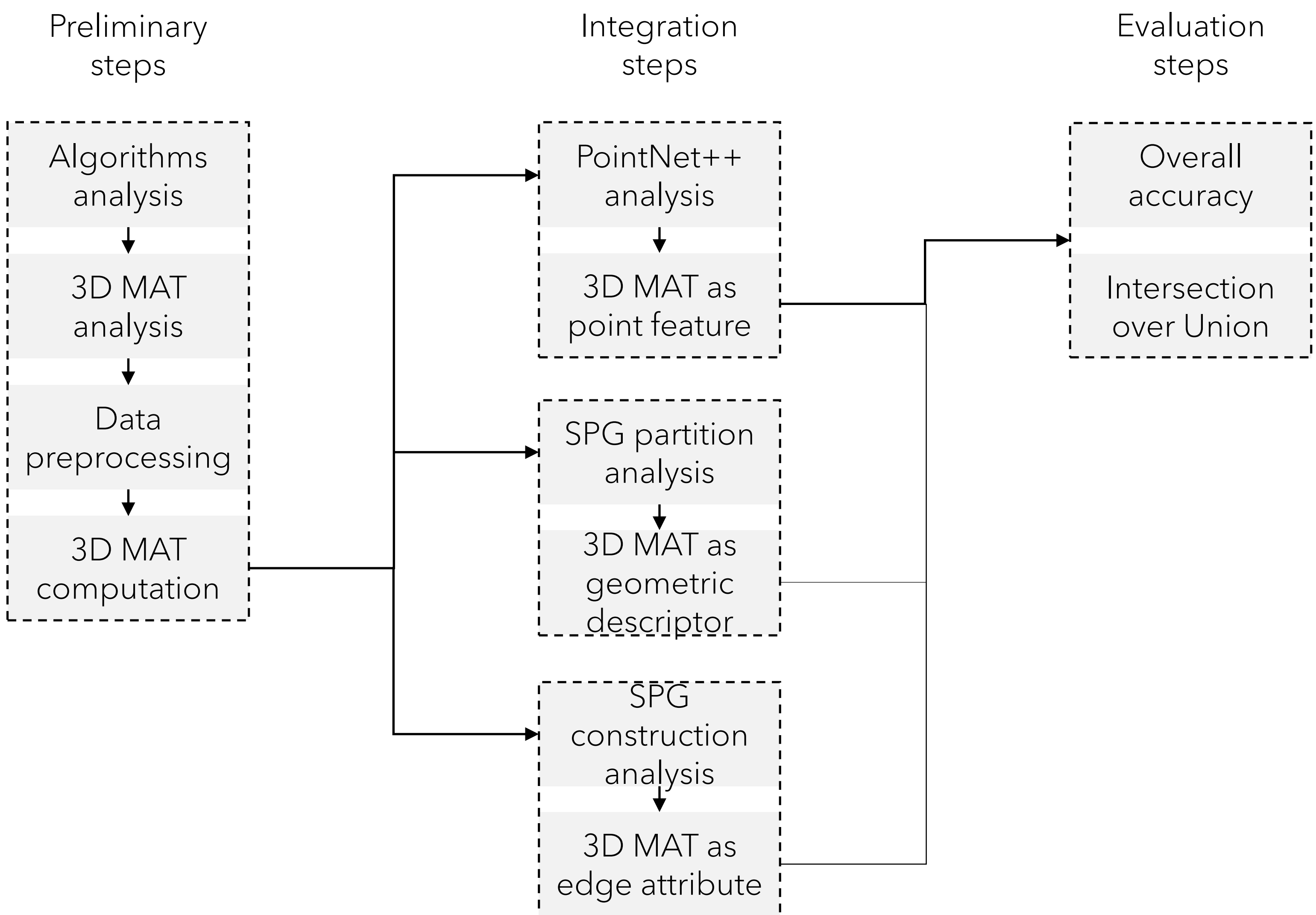
How can the properties of the 3D medial axis transform be exploited in deep learning algorithms for point cloud semantic segmentation?

3D MAT

- to give context to points
- to partition a point cloud
- to enrich a graph edges information

- most useful properties
- to improve the accuracy of deep learning methods
- performance real data-set vs synthetic data-set

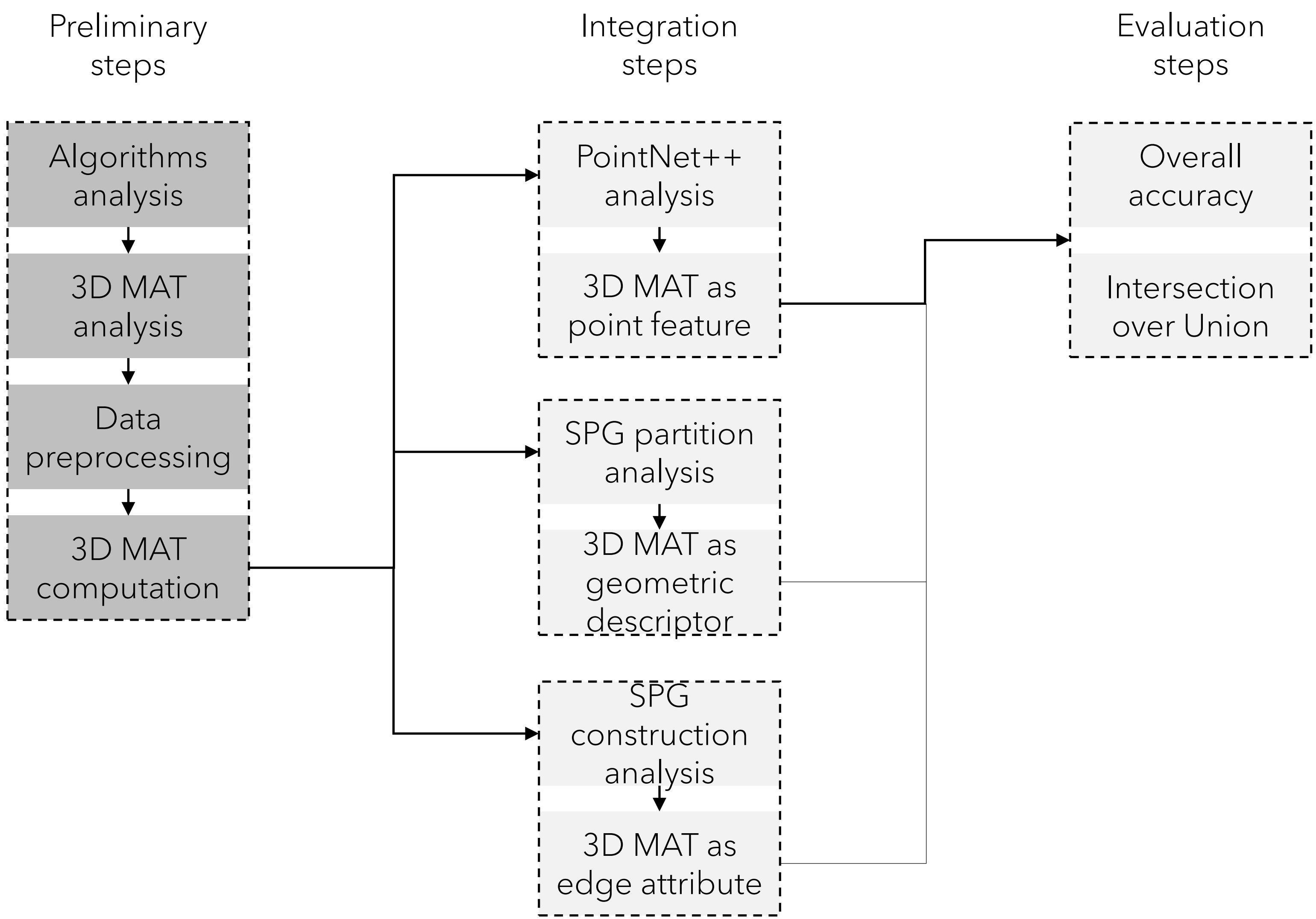
METHODOLOGY
Pipeline



TUDelft cyclomedia

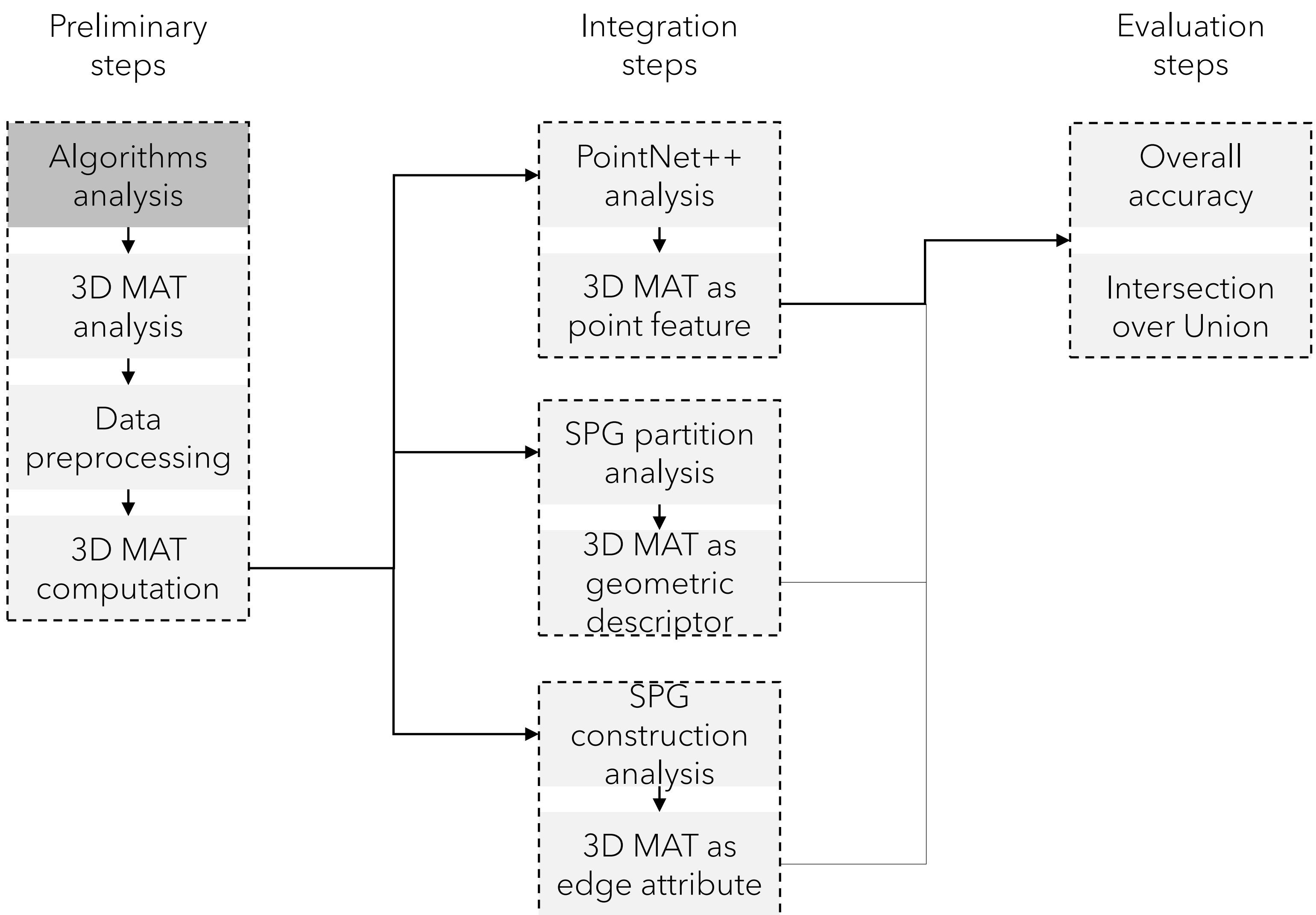
METHODOLOGY

Pipeline – preliminary steps



METHODOLOGY

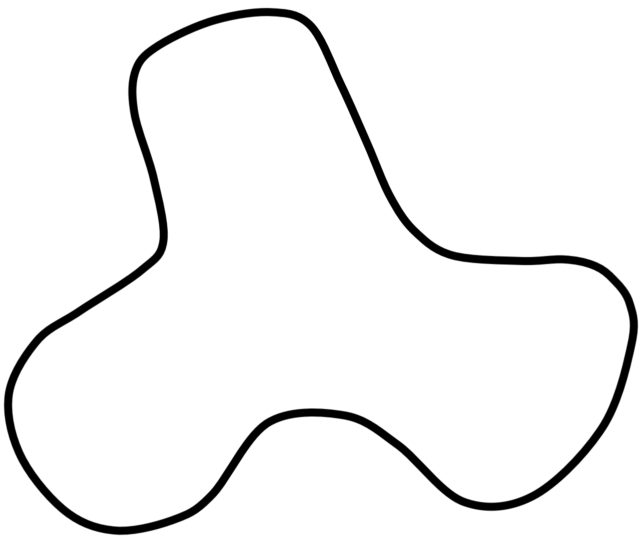
Pipeline – preliminary steps



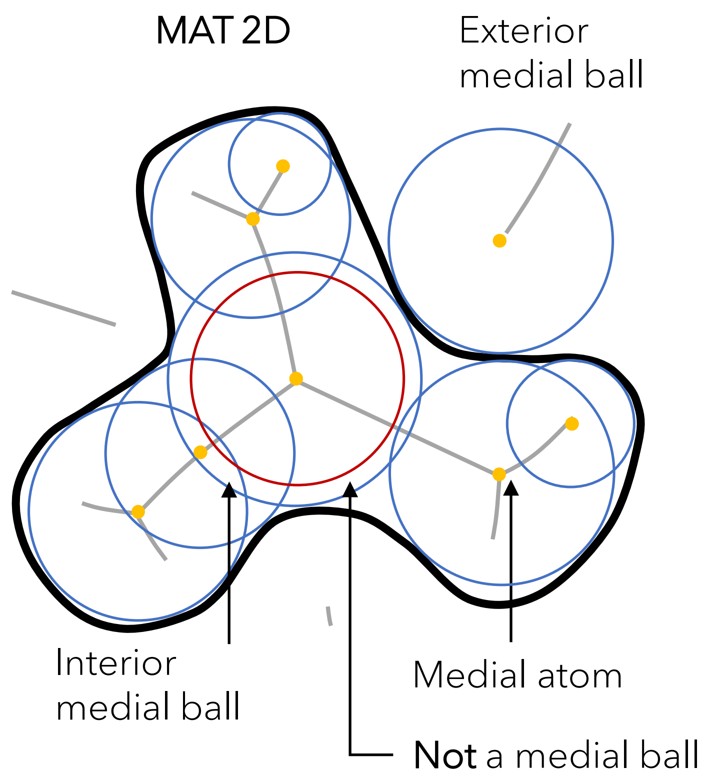
MEDIAL AXIS TRANSFORM
Definition

Skeleton representation of shapes, dual to the boundary of an object

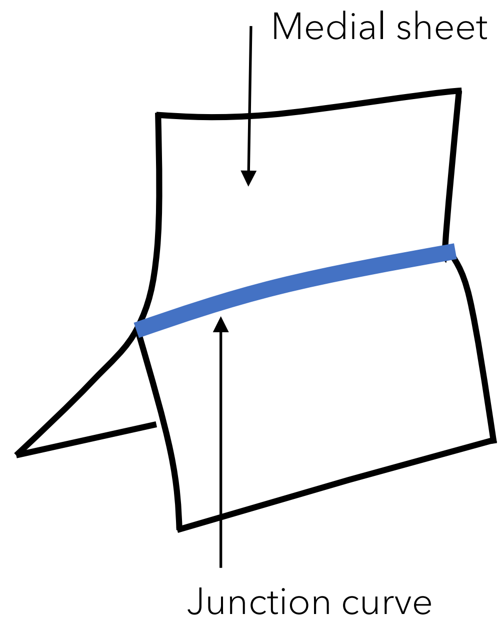
Object 2D



MAT 2D

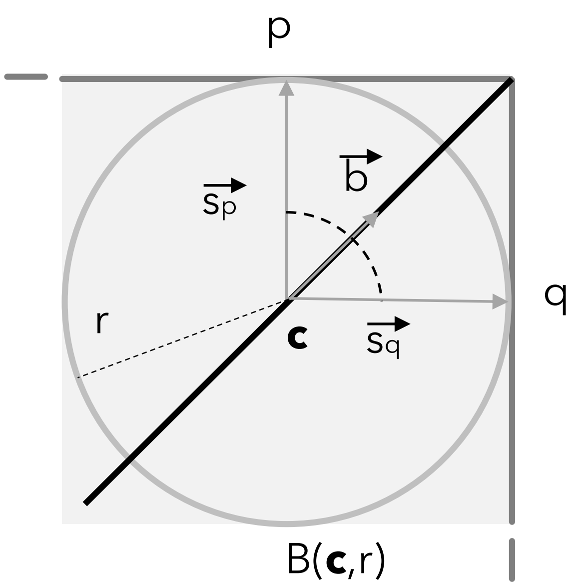


MAT 3D



Algorithms analysis → 3D MAT analysis → Data preprocessing → 3D MAT computation

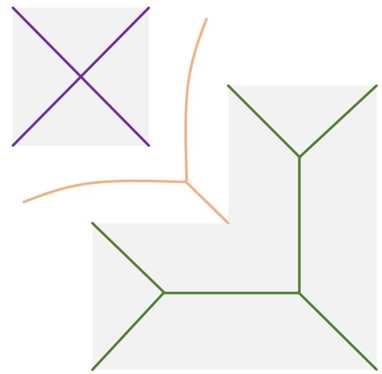
Point properties



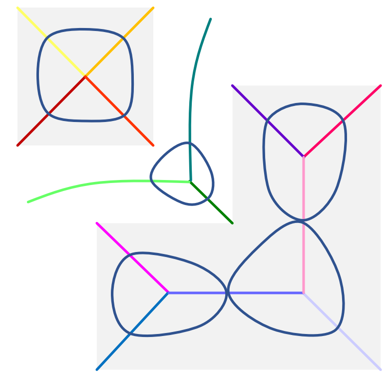
Geometry of the medial atom

p, q: feature points
c: medial point
r: radius
B(**c**,r) medial ball
sp, **sq**: spoke vectors
b: medial bisector
separation angle

Graph properties



Interior and exterior MAT



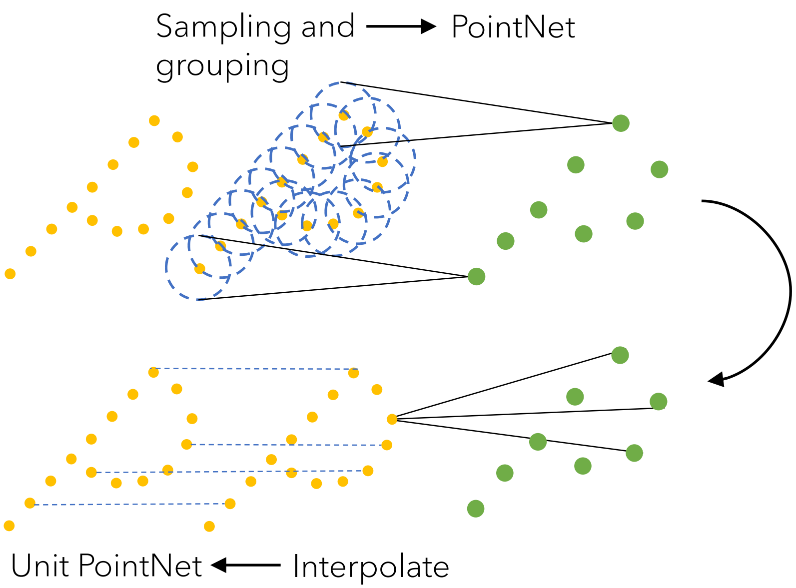
Structured MAT

Point based networks

PointNet++

Deep learning architecture

Hierarchical features learning



Segmentation – per point predictions

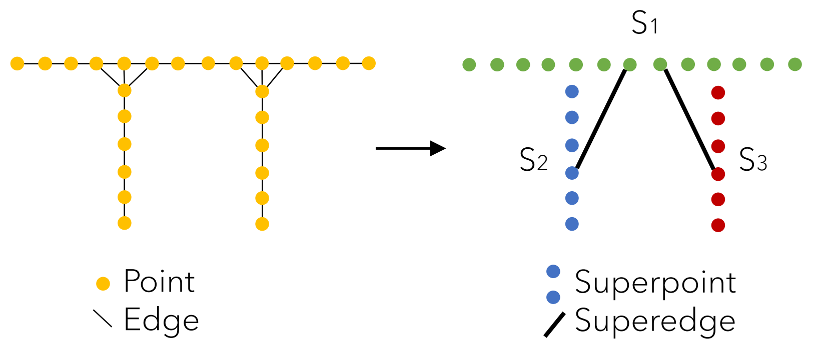
Graph based networks

Superpoint Graph

Preprocessing

Partition in simple shapes – Superpoints

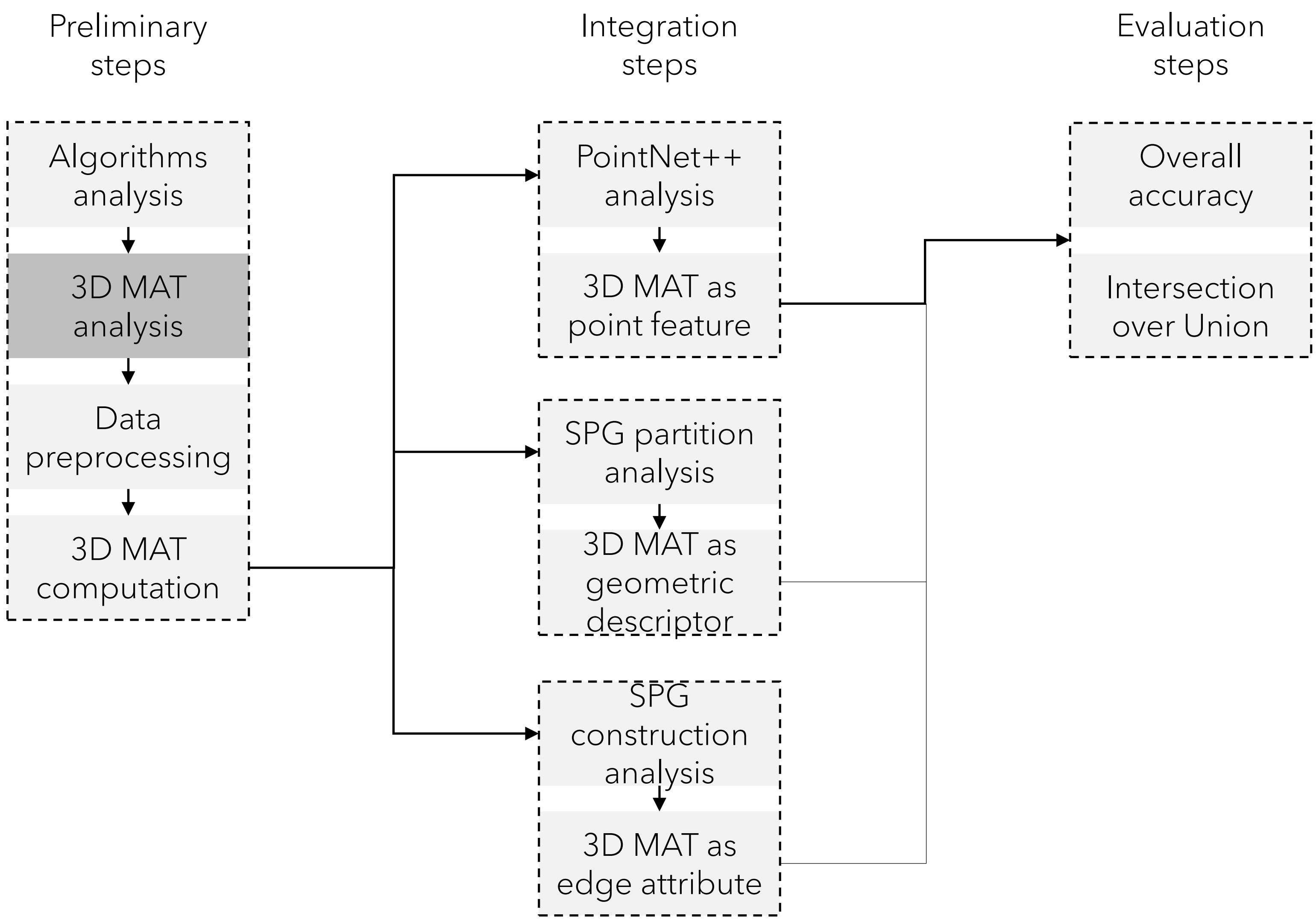
Construction of adjacency graph



Deep learning architecture

PointNet & graph convolution for predictions

METHODOLOGY
Pipeline – preliminary steps



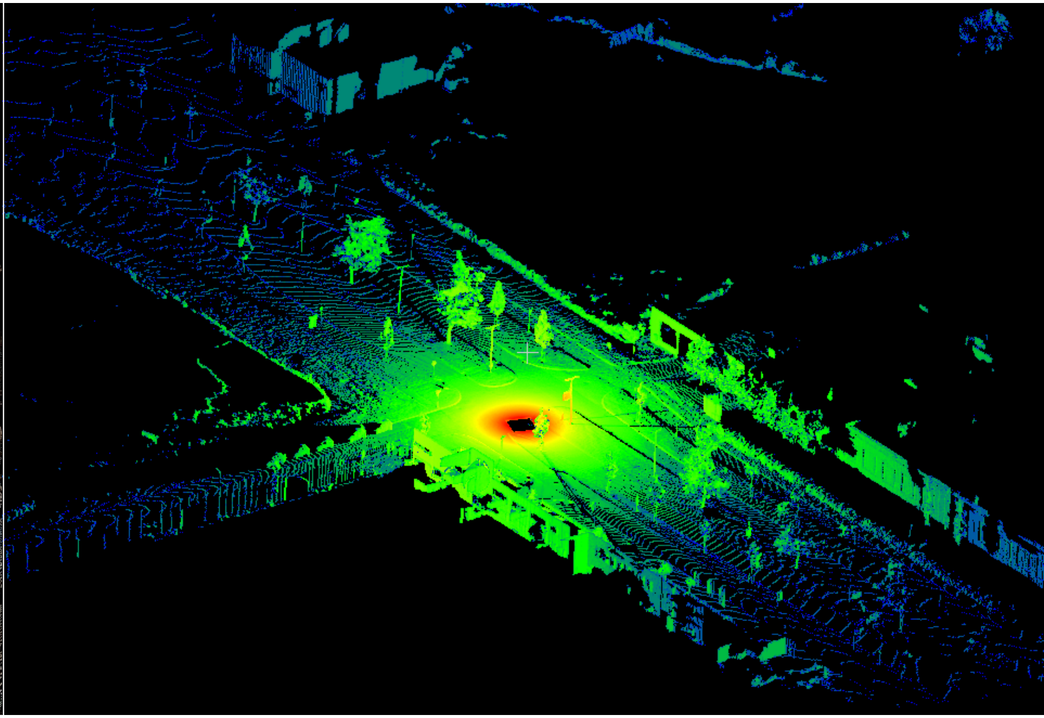
Internal dataset

Mobile laser scanner

80 point clouds – each 3 million points

6 semantic classes

One CycloMedia point cloud



One CycloMedia point cloud –
number of neighbors per point

Algorithms analysis → **3D MAT analysis** → Data preprocessing → 3D MAT computation

Datasets characteristics

MLS data-set

Low presence of noise

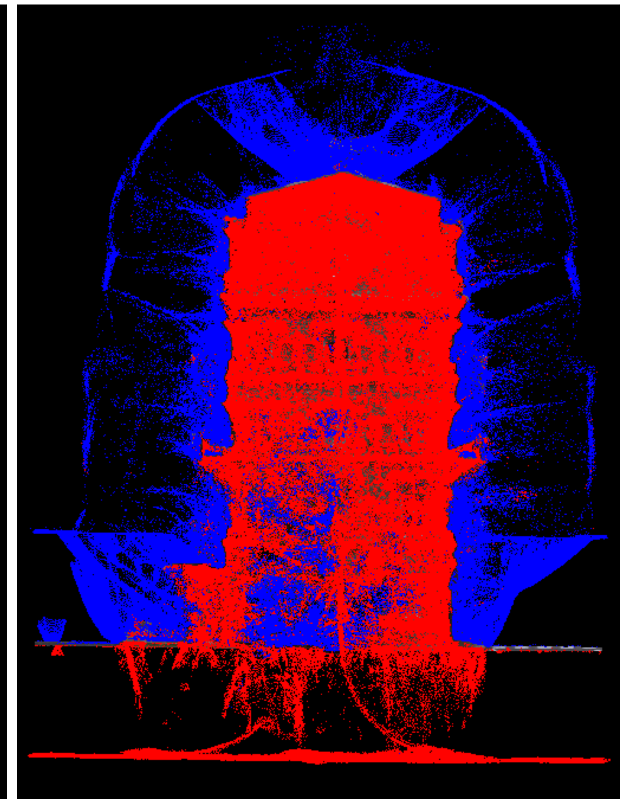
Low presence of artifacts

High points' density

Homogeneous points' density

Objects' geometry is fully represented

3DOM point cloud



3DOM point cloud – MAT

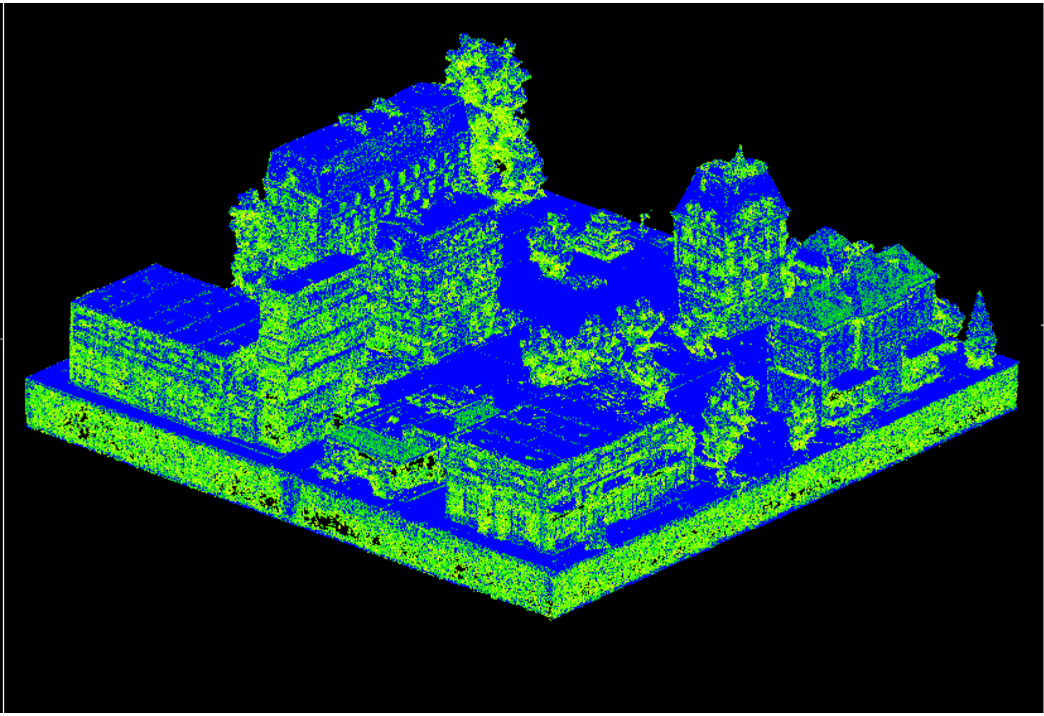
3DOM dataset

Dense image matching point cloud

1 point cloud – total 28 million points

6 semantic classes

3DOM point cloud



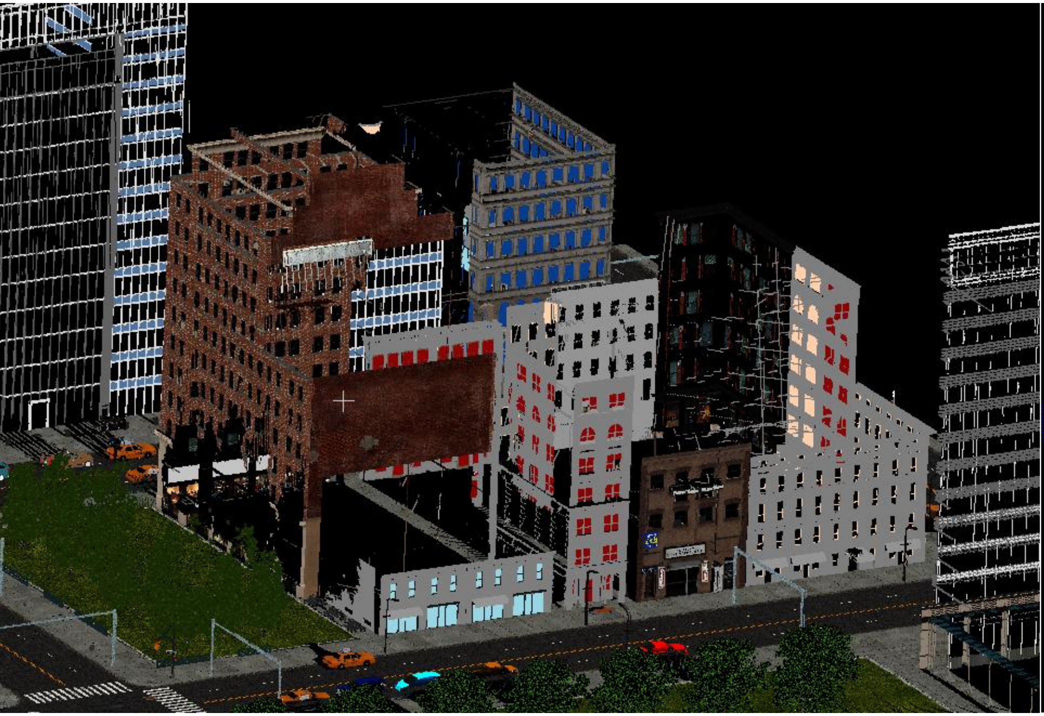
3DOM point cloud –
number of neighbors per point

SynthCity dataset

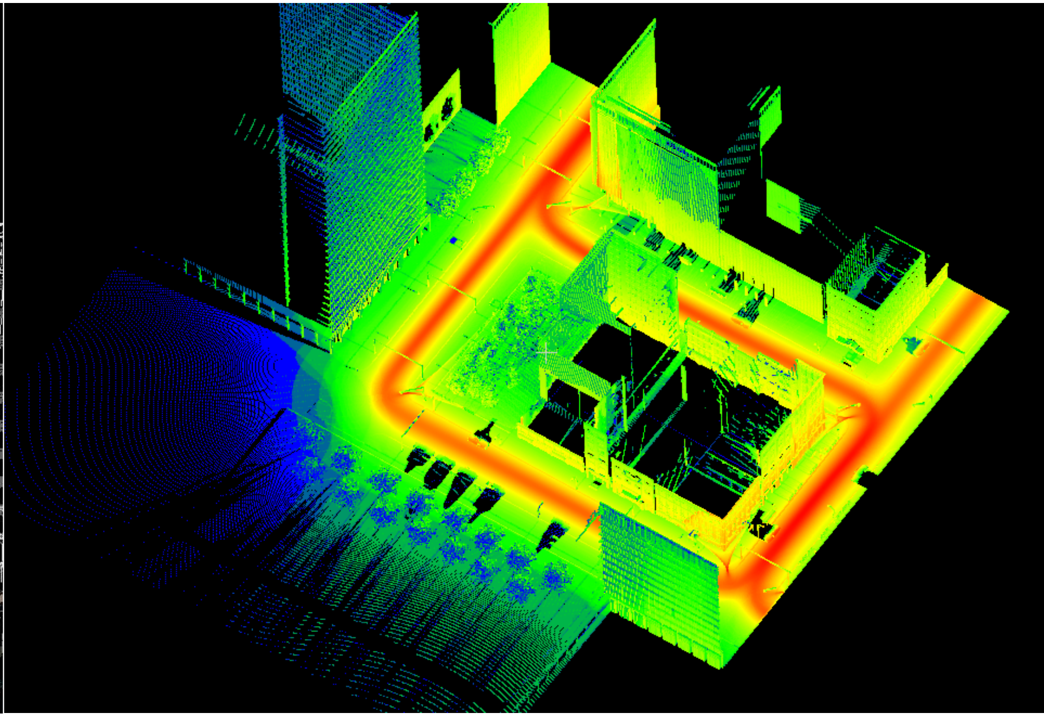
Simulated Velodyne scanner – mobile laser scanner

9 point clouds – total 368 million points

9 semantic classes



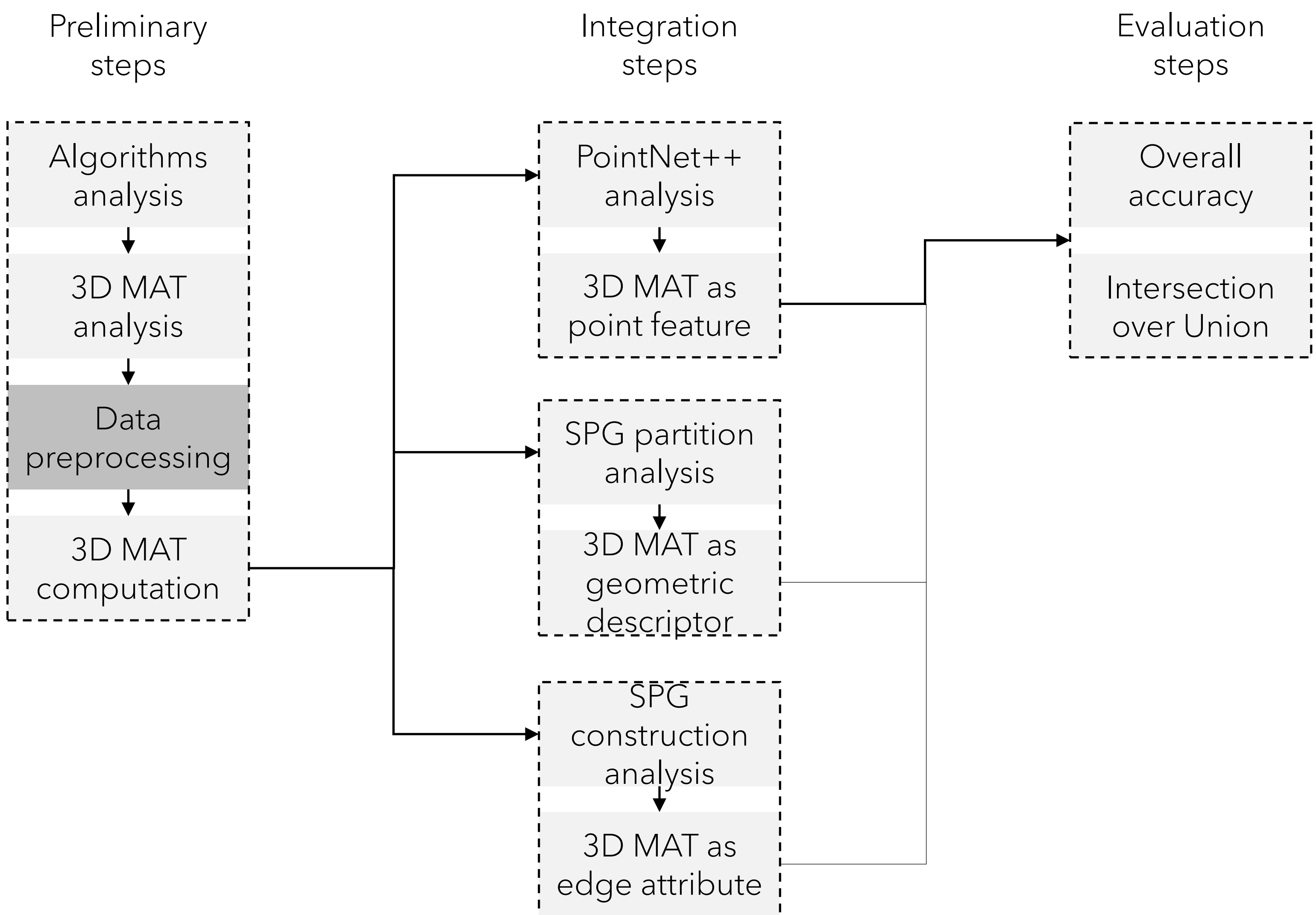
Subset of a SynthCity point cloud



Subset of a SynthCity point cloud – number of neighbors per point

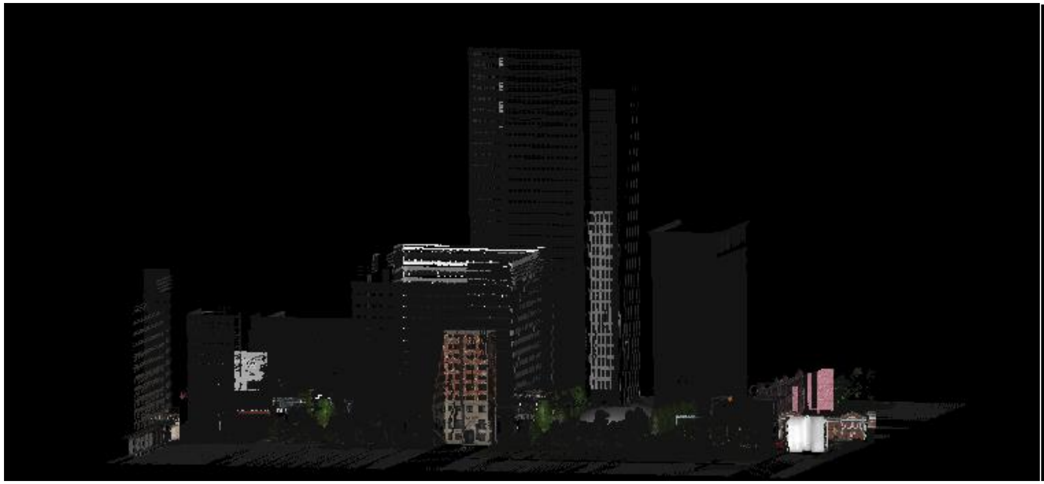
METHODOLOGY

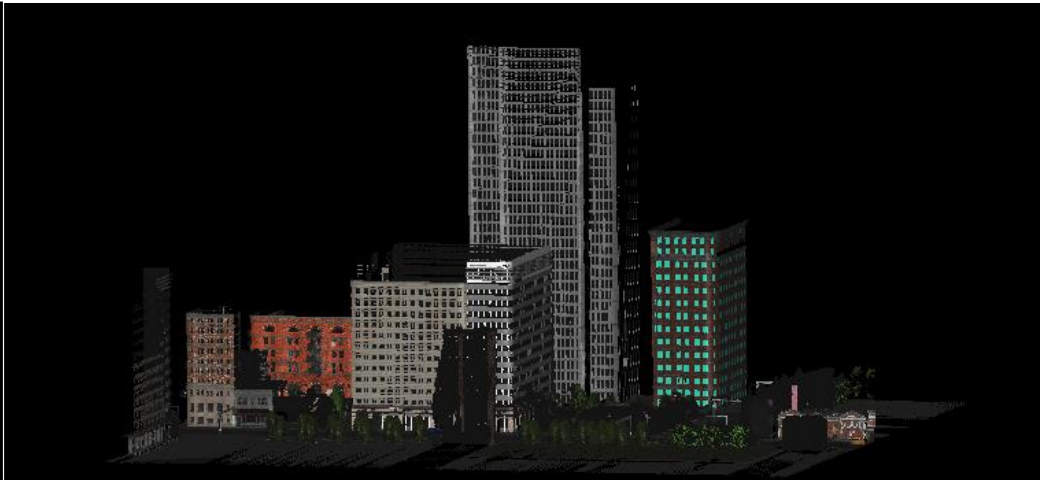
Pipeline – preliminary steps



METHODOLOGY
Preliminary steps

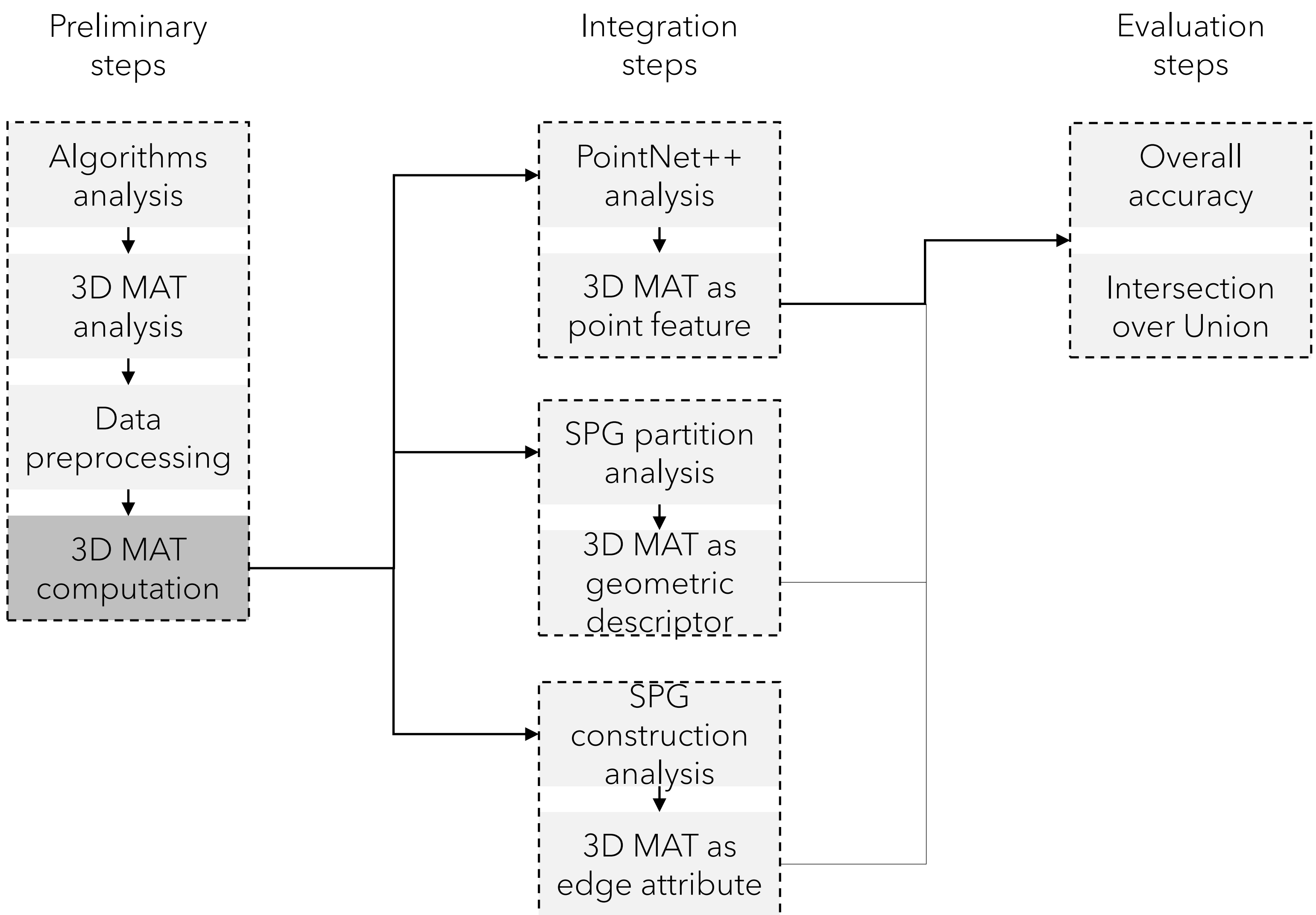
Algorithms analysis → 3D MAT analysis → **Data preprocessing** → 3D MAT computation


SynthCity – default normals


SynthCity – oriented normals

METHODOLOGY

Pipeline – preliminary steps



TU Delft cyclomedia

METHODOLOGY
Preliminary steps

Algorithms analysis → 3D MAT analysis → Data preprocessing → 3D MAT computation

3DOM point cloud – default MAT

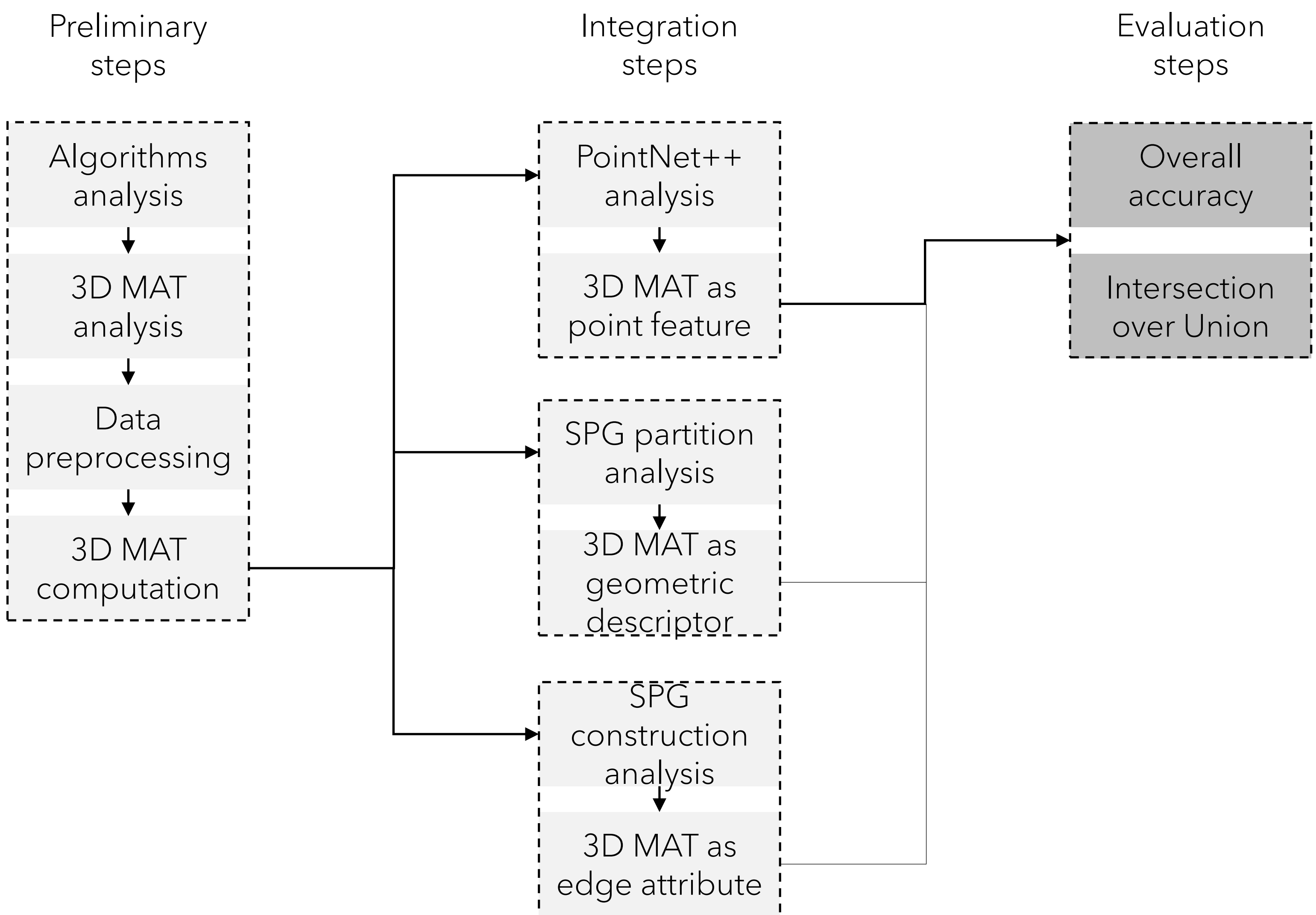
3DOM point cloud – custom MAT

MAT construction parameters
Denoise planar
Denoise preserve
Initial radius

MAT structuration parameters
Ball overlap
Bisector angle
K
Method
Minimum count
Separation angle
Shape count

METHODOLOGY

Pipeline – evaluation steps



METHODOLOGY
Evaluation steps

Overall accuracy

Intersection over Union

Confusion matrix

	A	B	C	D	
A	10	3	7	5	25
B	5	20	4	8	37
C	2	6	30	1	39
D	11	9	12	25	57
	28	38	53	39	158

True positives

Total

With respect to class A

False positives

False negatives

Overall accuracy (OA)

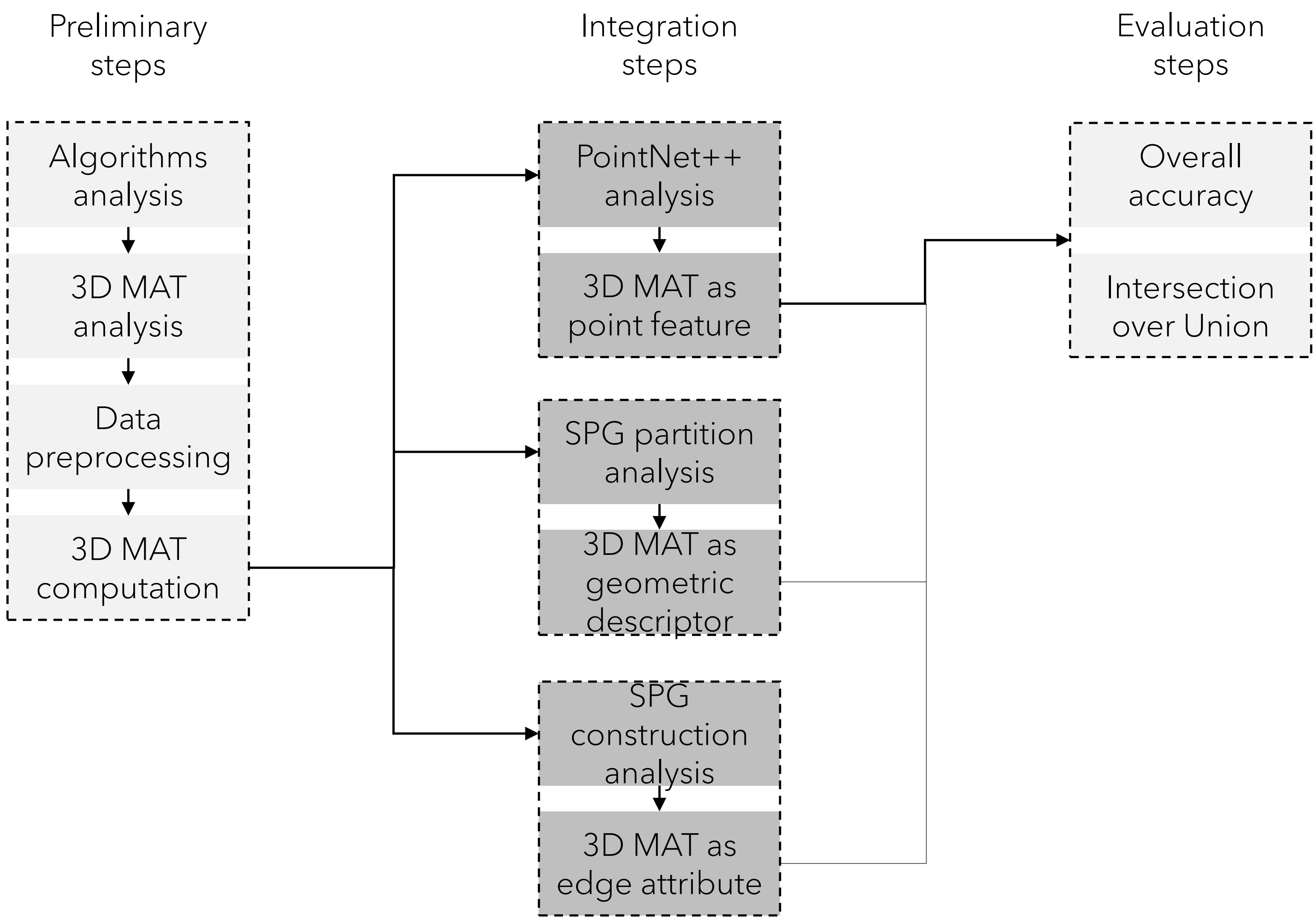
$$OA = \frac{85}{158}$$

Intersection over Union (IoU)

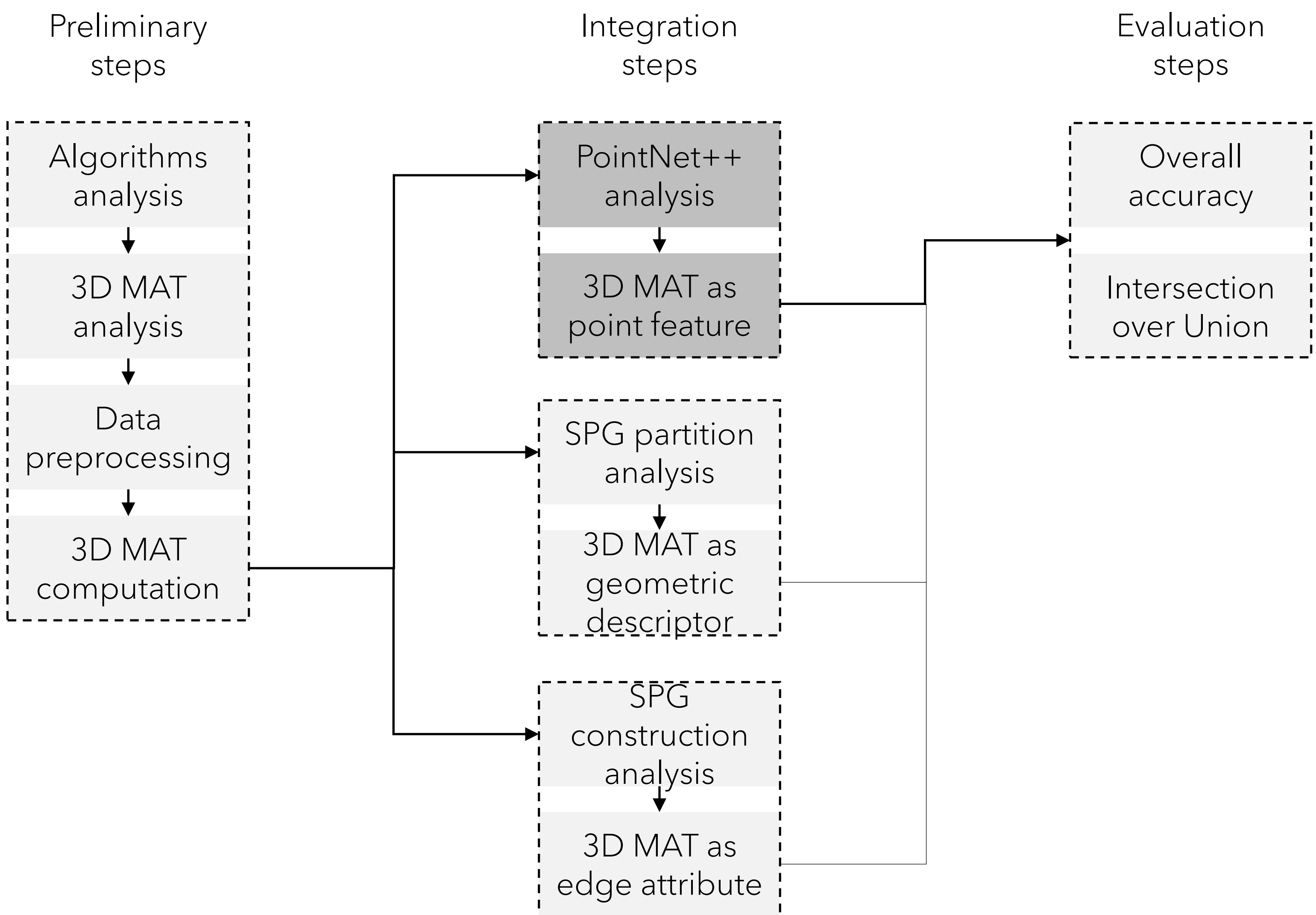
$$IoU = \frac{10}{18 + 15 + 10}$$

TU Delft cyclomedia

METHODOLOGY
Pipeline – integrated algorithm



METHODOLOGY
Pipeline – integrated algorithm

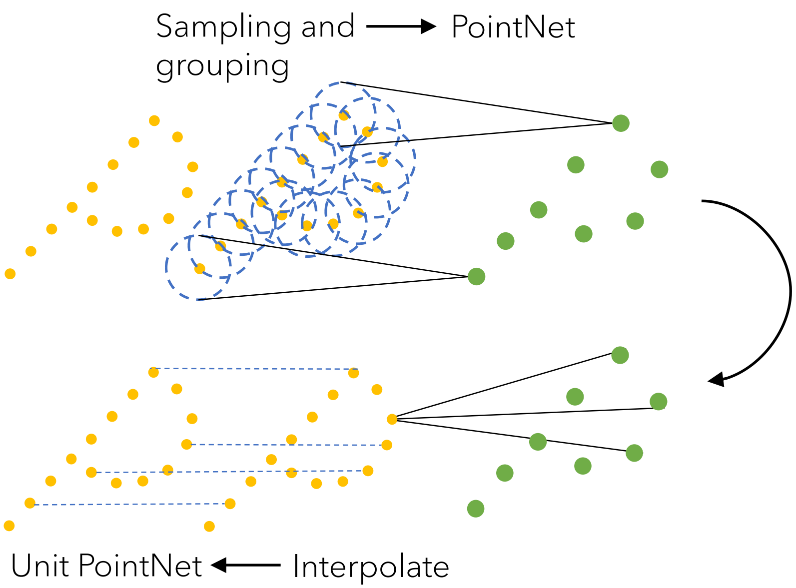


3D medial axis transform as a point feature
PointNet++ analysis

PointNet++

Deep learning architecture

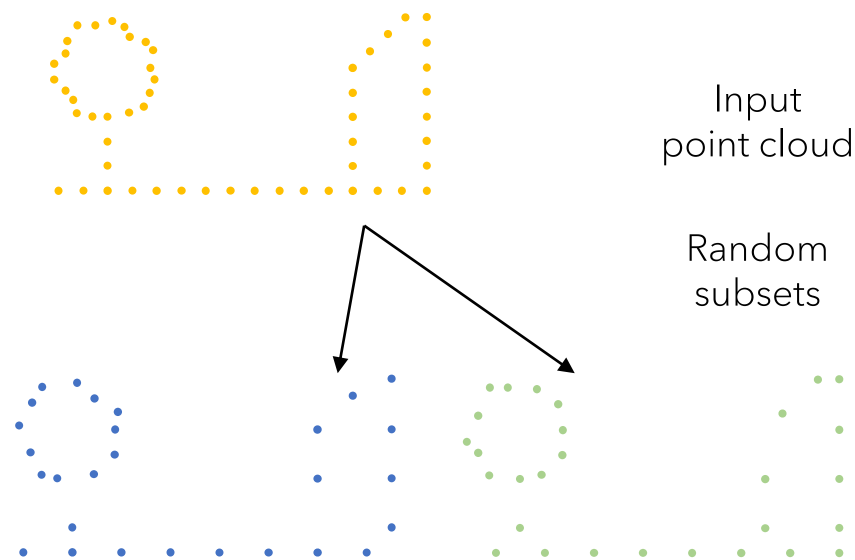
Hierarchical features learning



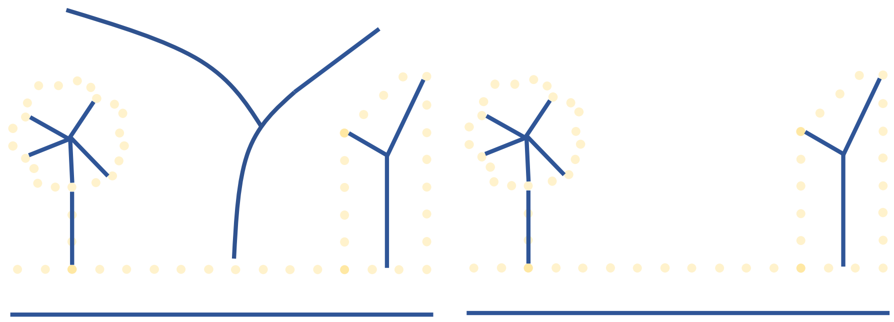
Segmentation – per point predictions

Algorithm's setting

<u>Batch size</u>	16
<u>Number of points</u>	9000
Learning rate	0.001
Epochs	200



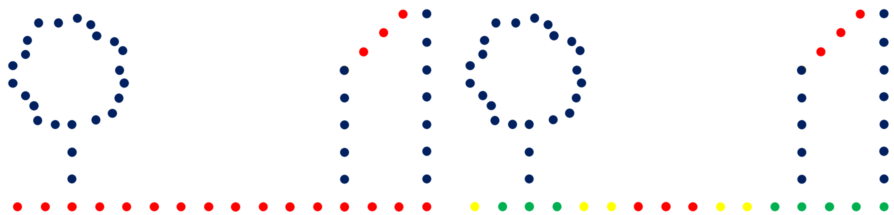
3D medial axis transform as a point feature
3D MAT use



Coordinates

3D MAT interior and exterior coordinates

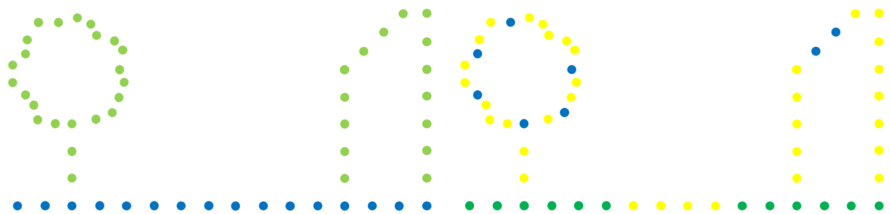
3D MAT interior coordinates



Local geometry of the medial atom

Interior radius

Exterior radius

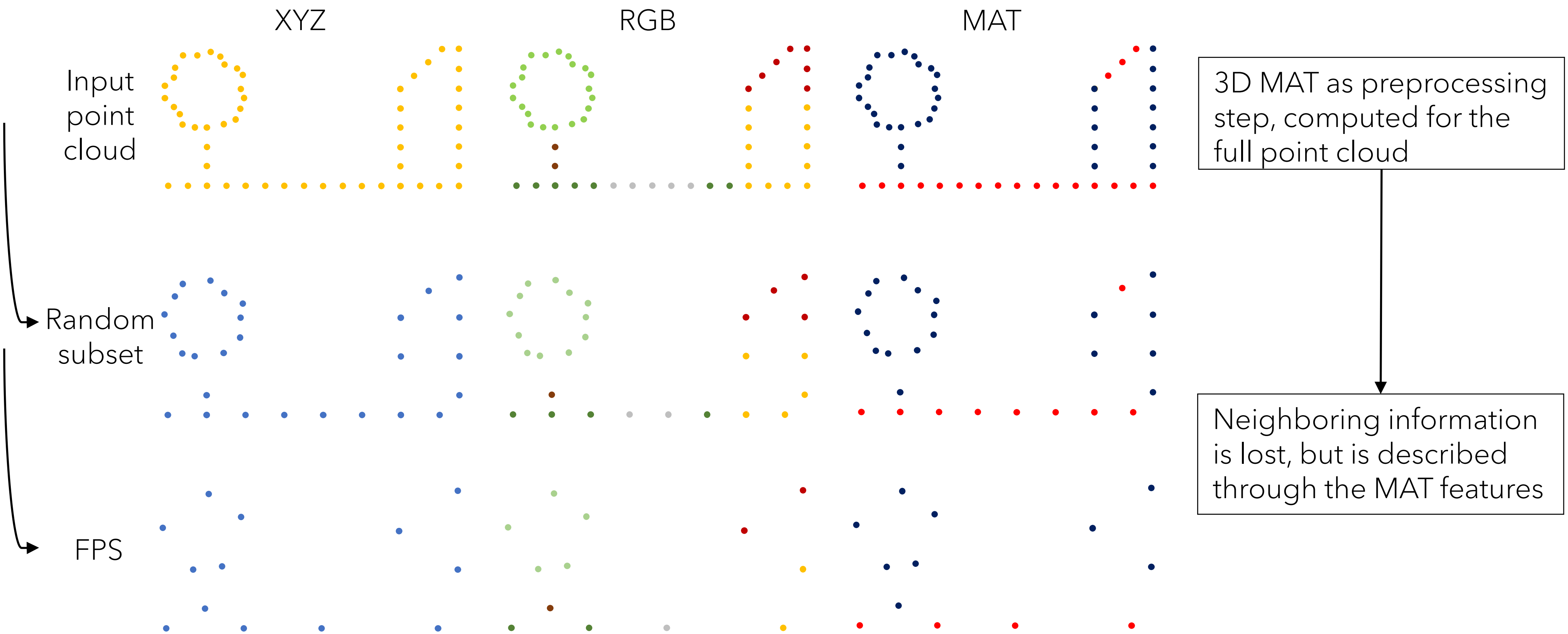


Interior separation angle

Exterior separation angle

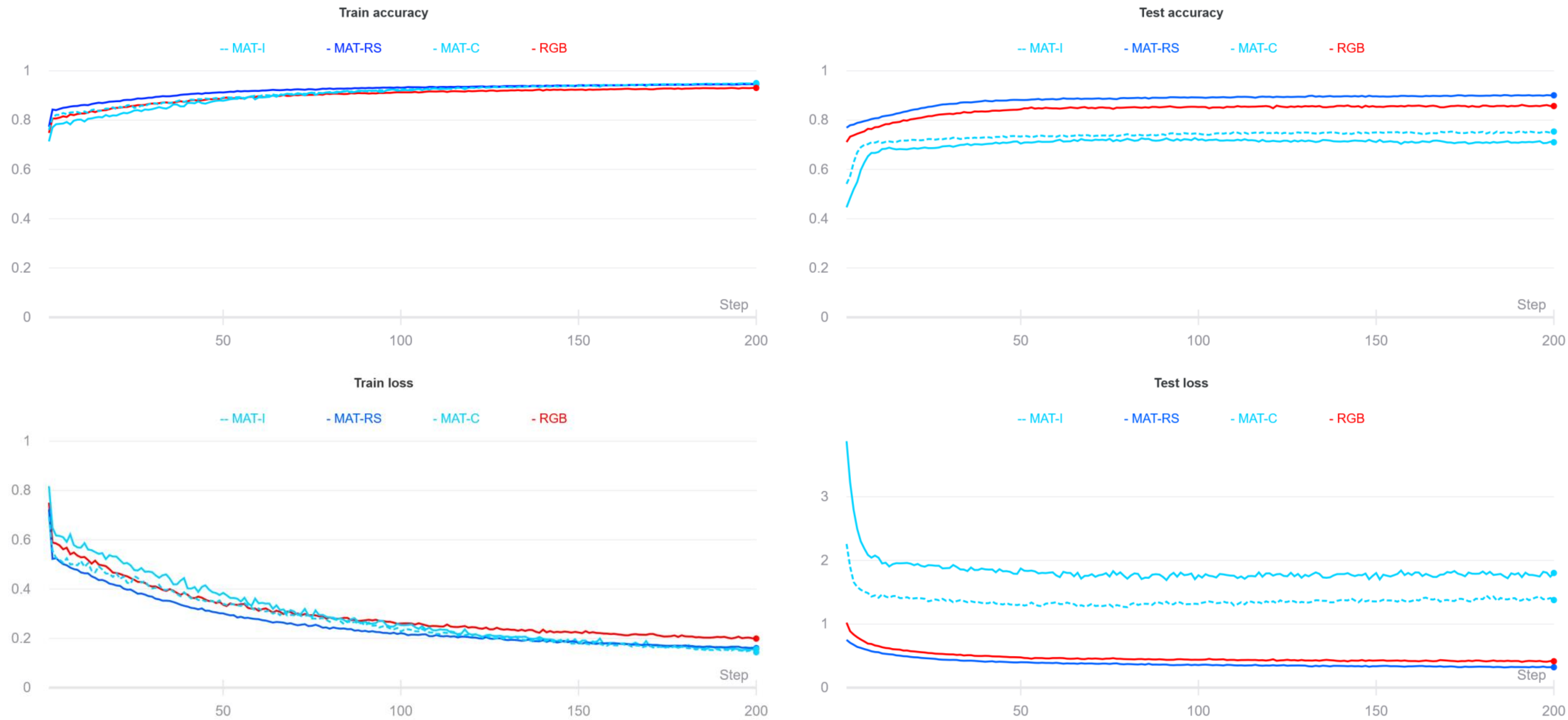
3D medial axis transform as a point feature

3D MAT use



3D medial axis transform as a point feature
3DOM – results

RGB	xyz + color
MAT-C	xyz + color + MAT coordinates
MAT-I	xyz + color + MAT interior coordinates
MAT-RS	xyz + color + radii and separation angles



TU Delft cyclomedia

3D medial axis transform as a point feature
3DOM – results

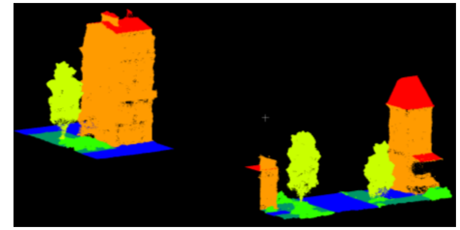
RGB	xyz + color
MAT-C	xyz + color + MAT coordinates
MAT-I	xyz + color + MAT interior coordinates
MAT-RS	xyz + color + radii and separation angles

	RGB	MAT-C		MAT-I		MAT-RS	
OA	0.86	0.69		0.72		0.91	
IoU							
Ground	74.48%	59.12%	-15.36	75.80%	+1.32	83.98%	+9.50
Grass	34.49%	15.40%	-19.09	14.39%	-20.10	67.84%	**+33.35**
Shrub	42.78%	22.50%	-20.28	22.47%	-20.31	66.52%	**+23.74**
Tree	86.38%	50.27%	**-36.11**	50.46%	**-35.92**	91.34%	+4.96
Façade	88.48%	60.43%	**-28.05**	61.91%	**-26.57**	89.18%	+0.70
Roof	59.94%	57.32%	-2.62	63.75%	+3.81	68.59%	+8.65

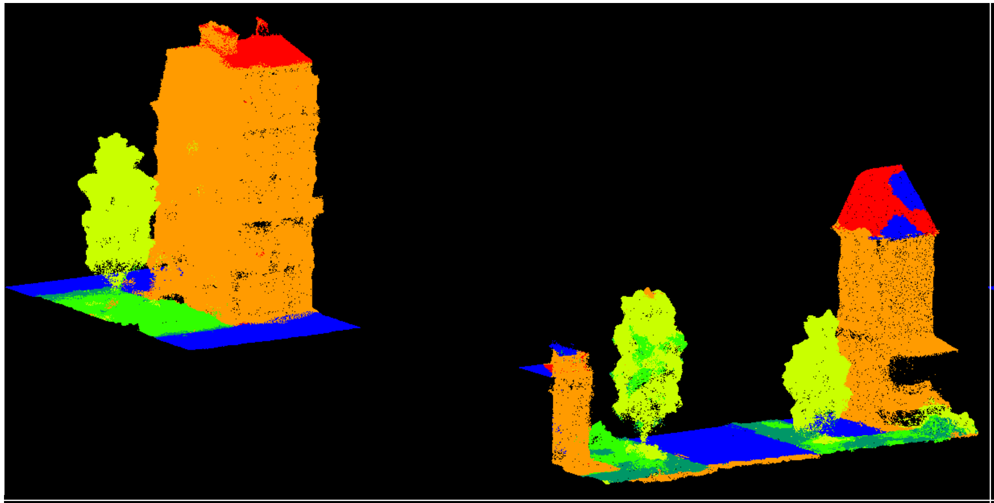
TU Delft cyclomedia

3D medial axis transform as a point feature
3DOM – results

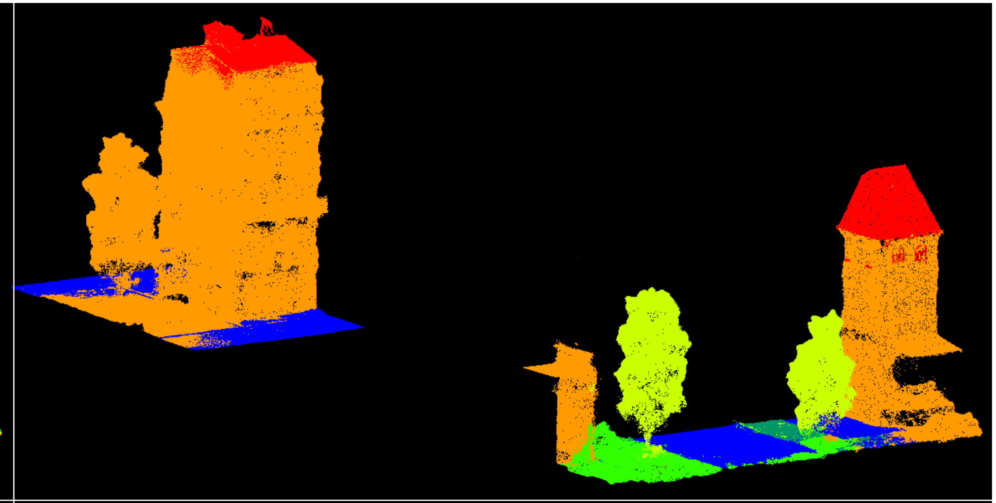
Ground truth

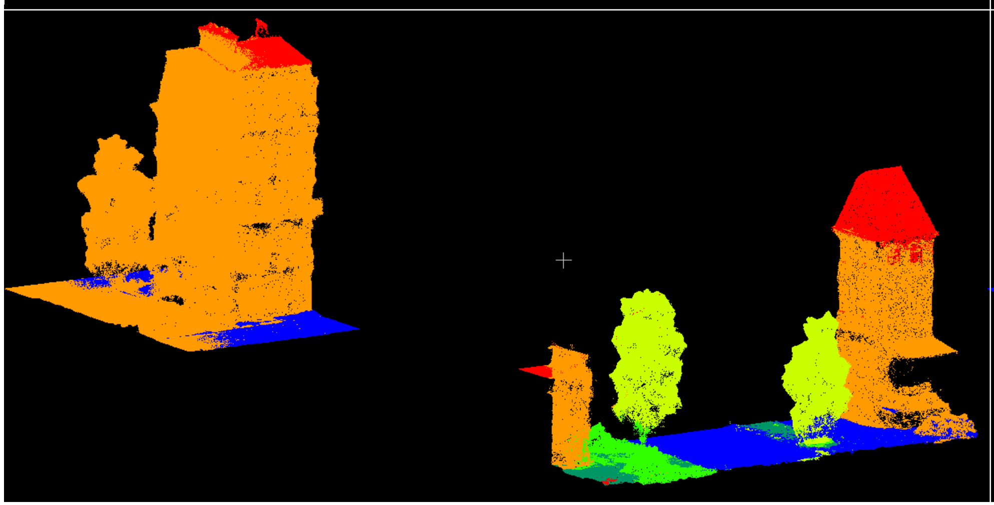


RGB classification point cloud

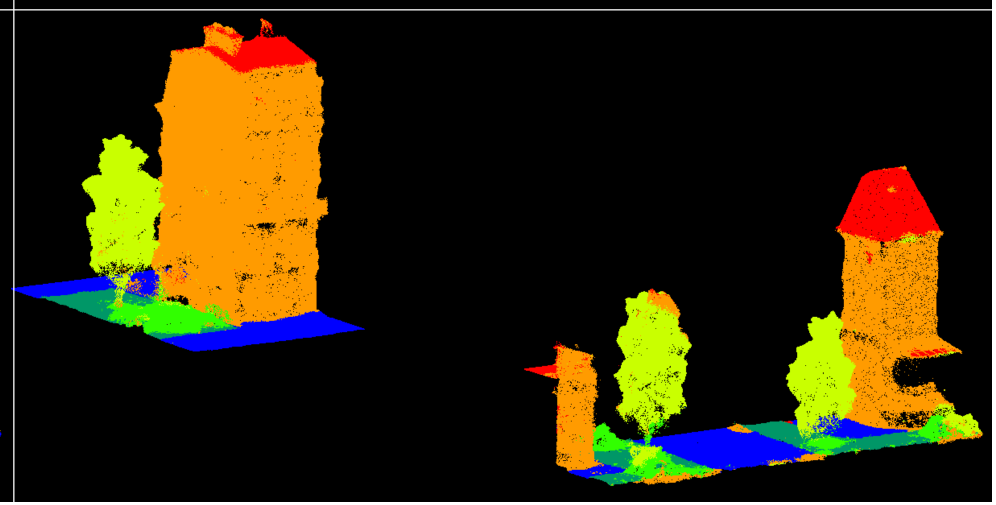


MAT interior coordinates classification point cloud





MAT coordinates classification point cloud

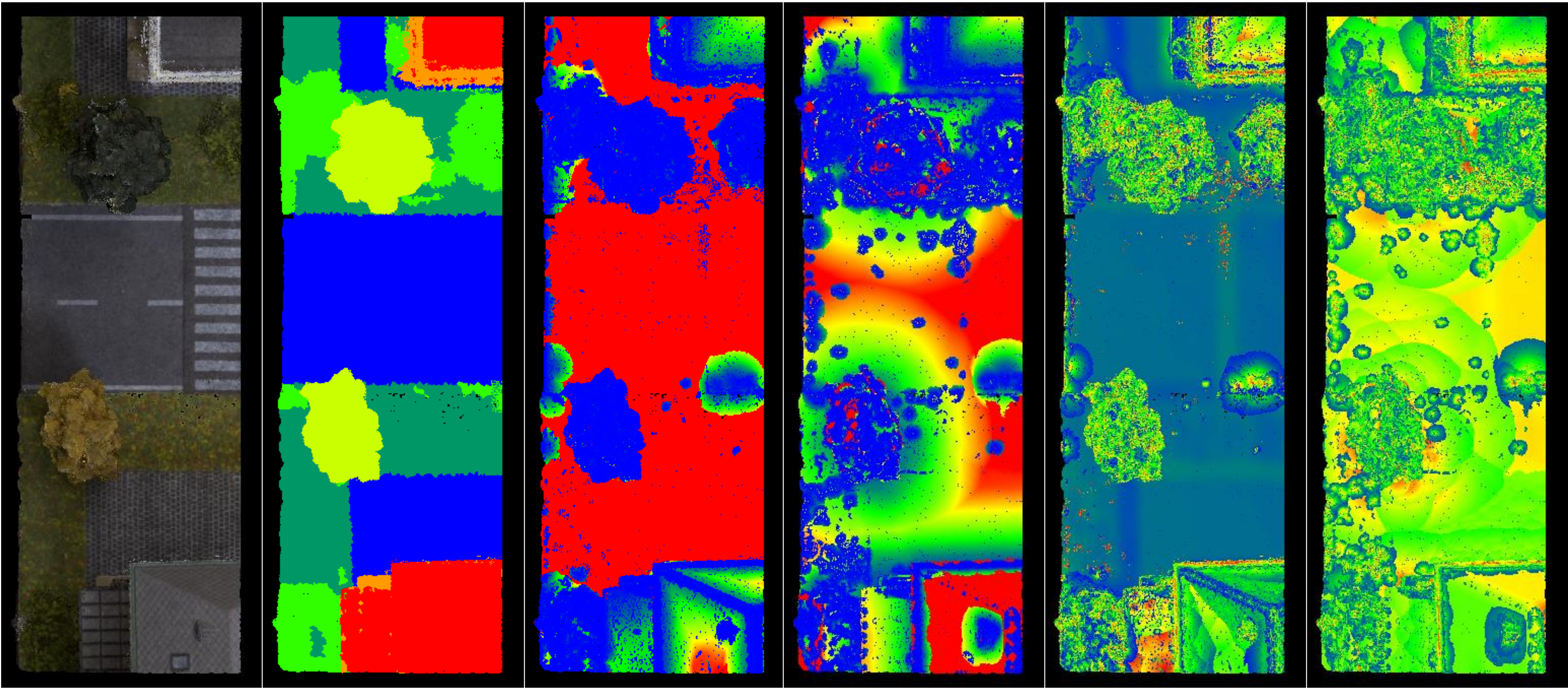


Radius and separation angle classification point cloud

TU Delft cyclomedia

3D medial axis transform as a point feature

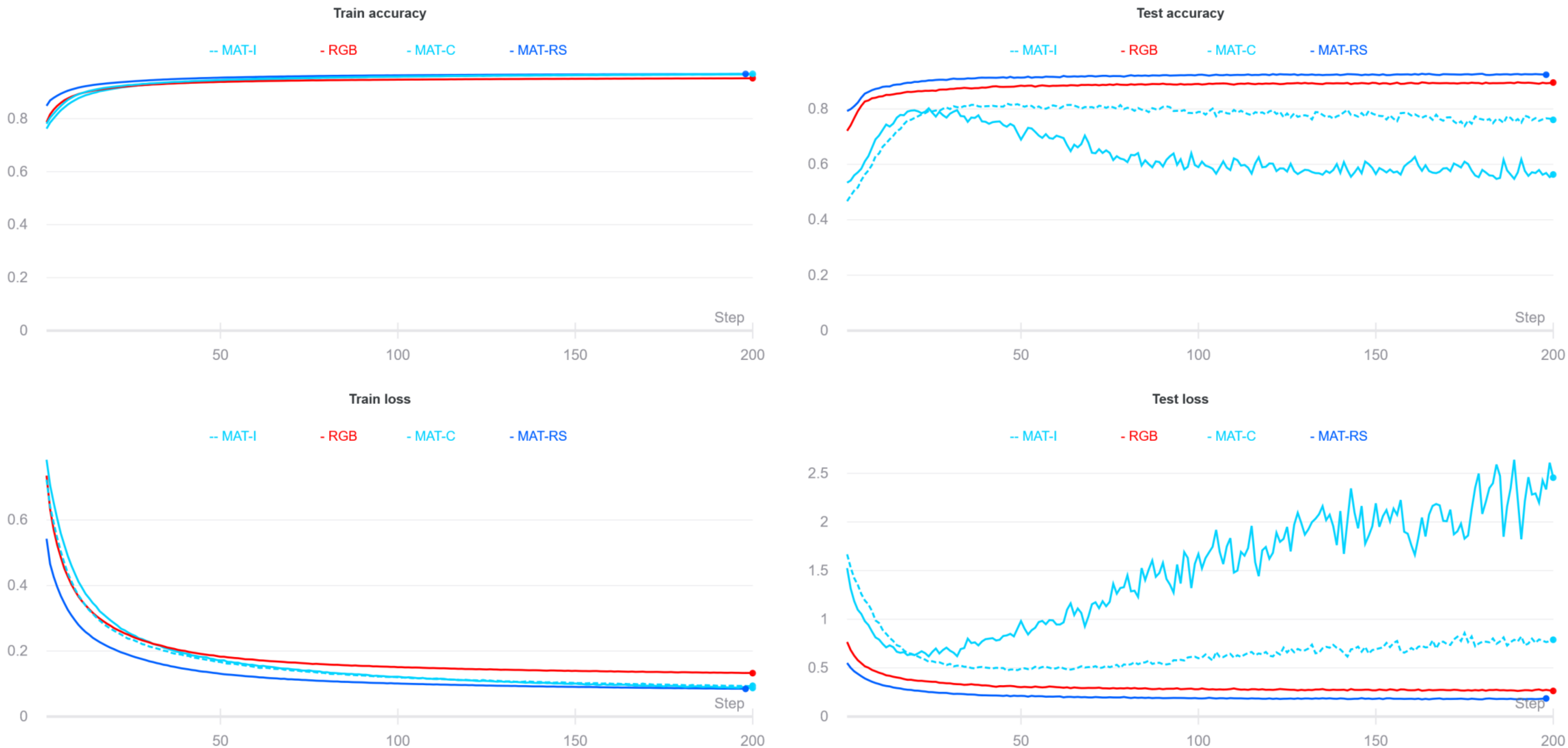
3DOM – analysis of results



RGB | Classification | Radius 1 | Radius 2 | Separation angle 1 | Separation angle 2

3D medial axis transform as a point feature
SynthCity – results

RGB	xyz + color
MAT-C	xyz + color + MAT coordinates
MAT-I	xyz + color + MAT interior coordinates
MAT-RS	xyz + color + radii and separation angles



3D medial axis transform as a point feature
SynthCity – results

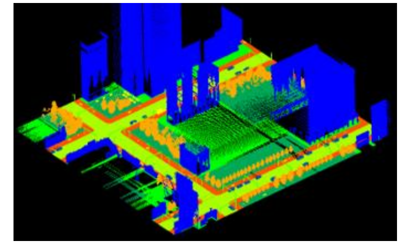
RGB	xyz + color
MAT-C	xyz + color + MAT coordinates
MAT-I	xyz + color + MAT interior coordinates
MAT-RS	xyz + color + radii and separation angles

	RGB	MAT-C		MAT-I		MAT-RS	
OA	0.94	0.86		0.88		0.96	
IoU							
Building	97.90%	90.64%	-7.26	92.04%	-5.86	98.89%	+0.99
Car	71.58%	14.08%	**-57.50**	24.27%	**-47.31**	78.71%	+7.31
Natural ground	84.92%	50.53%	-34.39	76.10%	-8.82	93.16%	**+8.24**
Ground	45.49%	8.48%	-37.01	15.13%	-30.36	56.82%	**+11.33**
Pole-like	65.72%	0.00%	**-65.72**	9.37%	**-56.35**	66.84%	+1.12
Road	96.41%	83.46%	-12.95	88.31%	-8.10	97.99%	+1.58
Street furniture	34.50%	0.00%	-34.50	0.31%	-34.19	41.03%	+6.53
Tree	88.18%	69.98%	-18.20	74.22%	-13.96	95.58%	**+7.40**
Pavement	72.04%	65.03%	-7.01	62.34%	-11.70	78.83%	+6.79

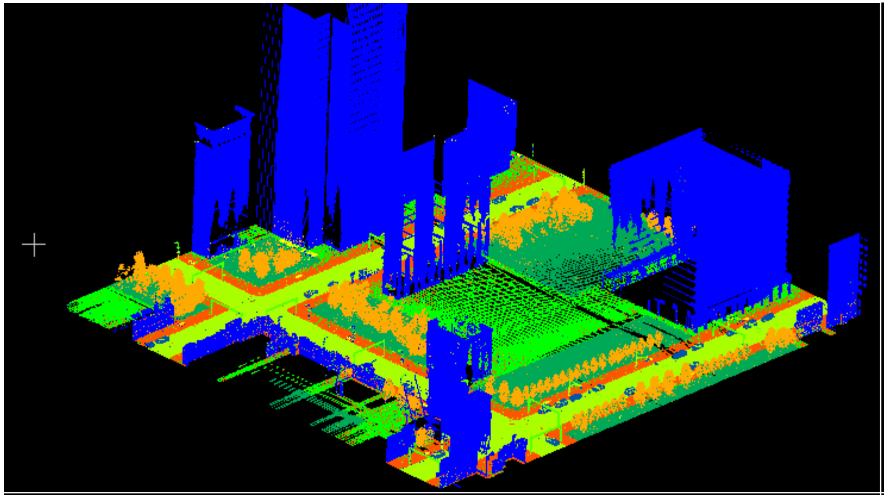
3D medial axis transform as a point feature

SynthCity – results

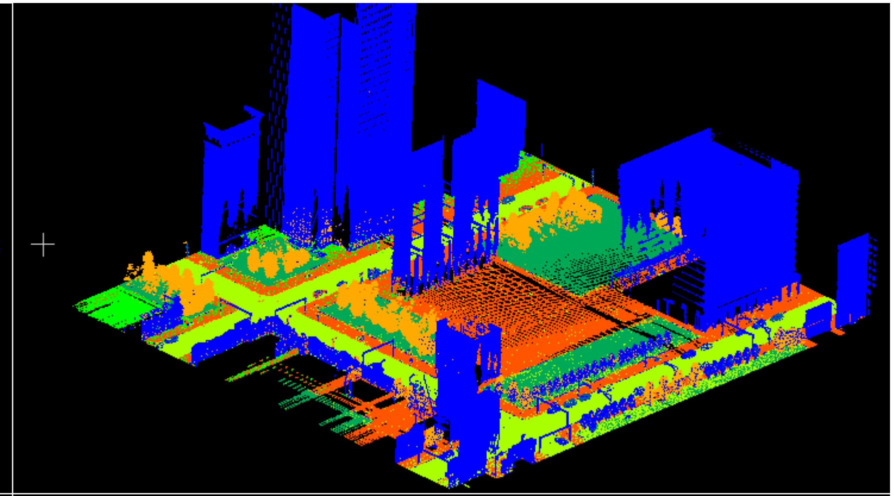
Ground truth

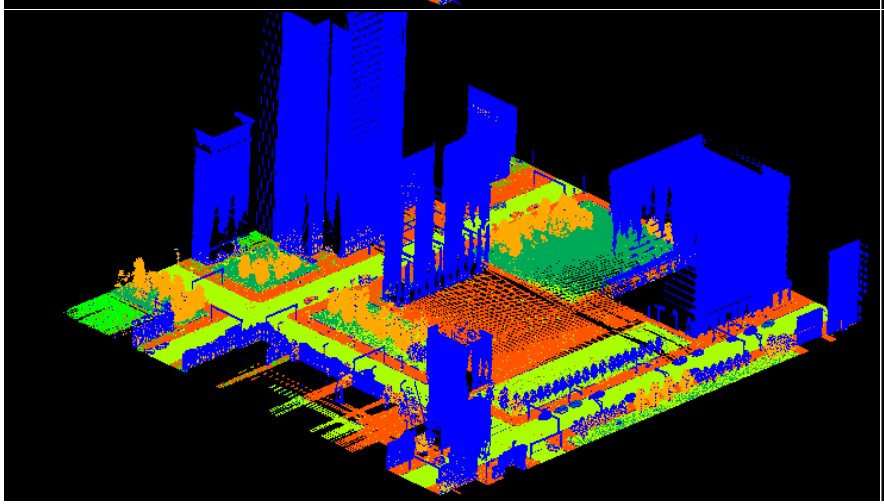


RGB classification point cloud

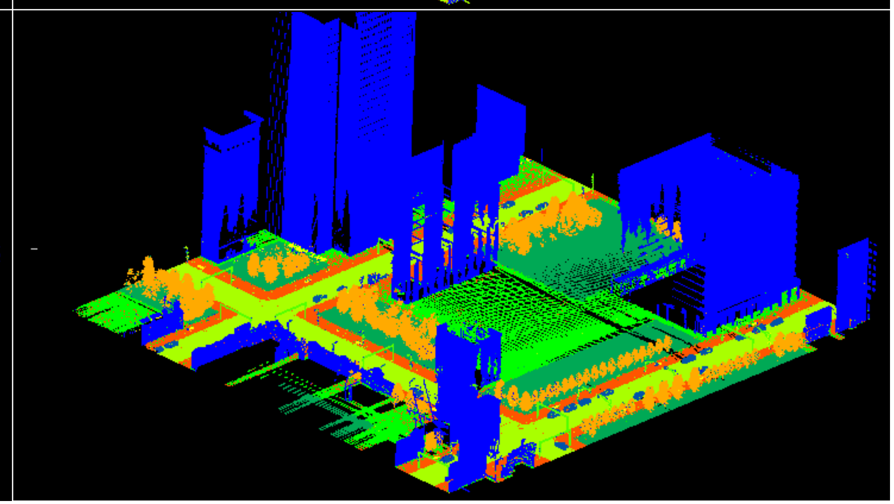


MAT interior coordinates classification point cloud





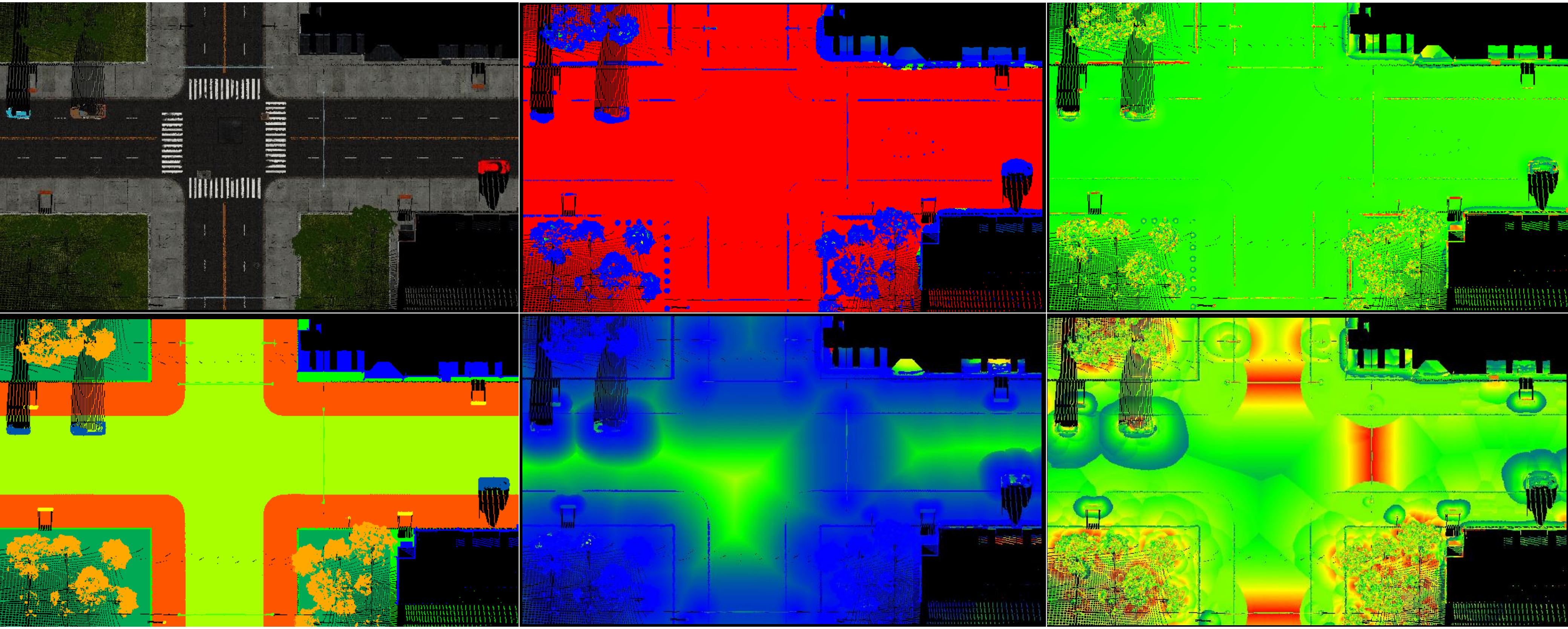
MAT coordinates classification point cloud



Radius and separation angle classification point cloud

3D medial axis transform as a point feature
SynthCity – analysis of results

RGB | Radius 1 | Separation angle 1

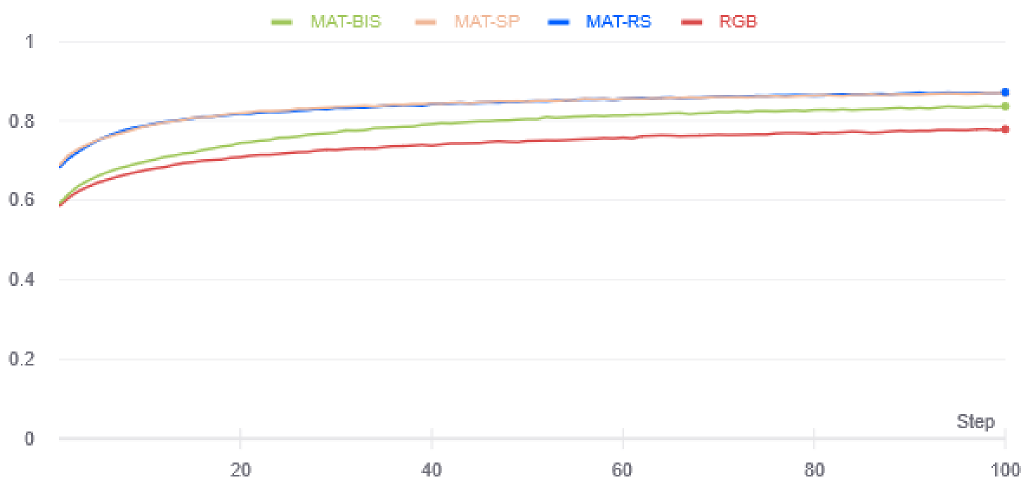


Classification | Radius 2 | Separation angle 2

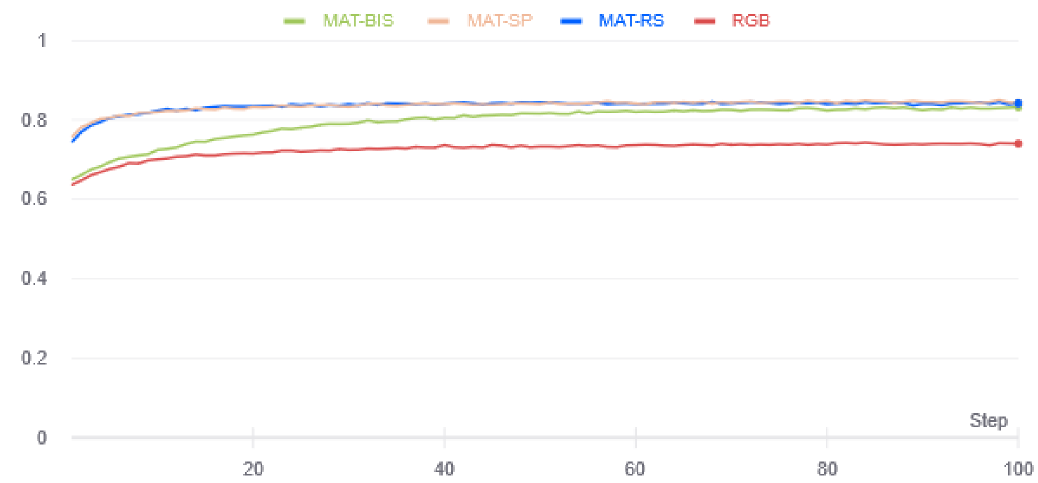
3D medial axis transform as a point feature
Internal dataset – results

RGB	xyz + color
MAT-RS	xyz + color + radii and separation angles
MAT-SP	xyz + color + spoke vectors
MAT-BIS	xyz + color + bisector angles

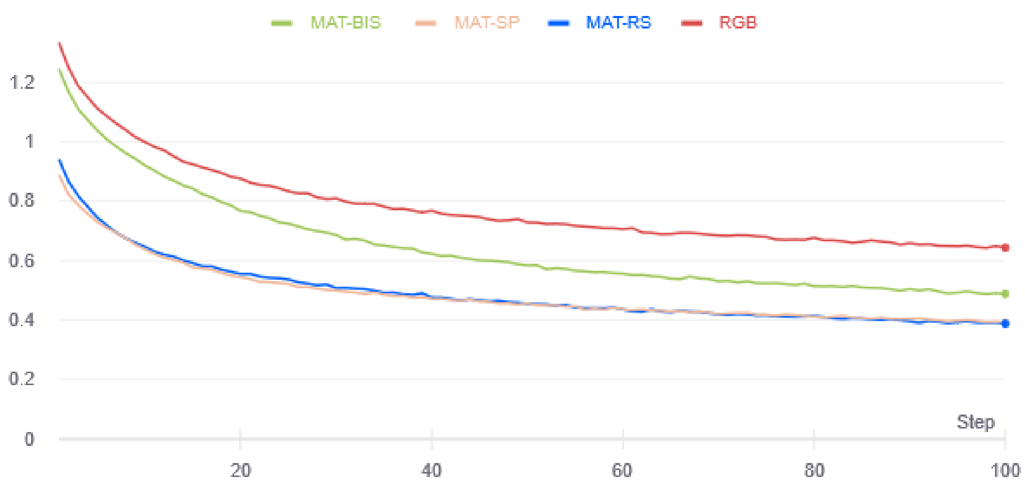
Train accuracy



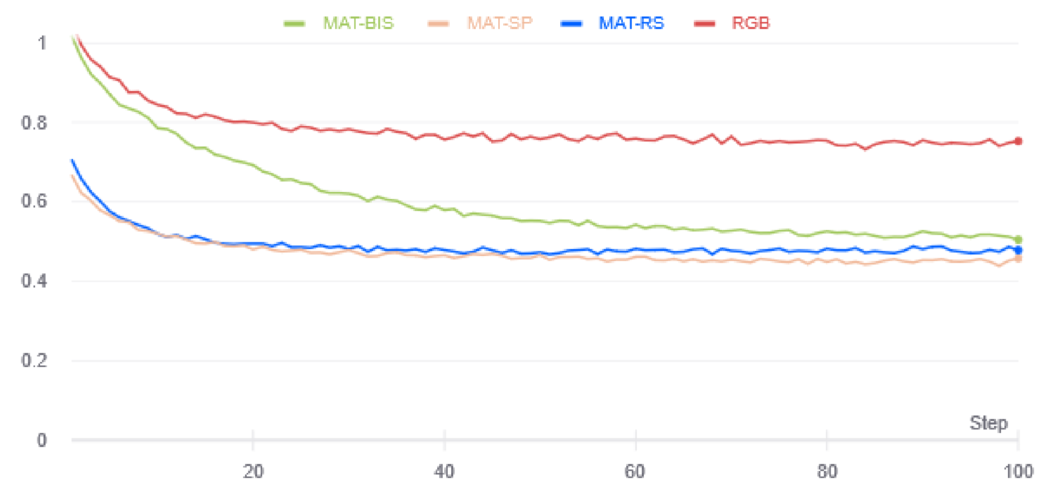
Test accuracy



Train loss



Test loss



TU Delft cyclomedia

3D medial axis transform as a point feature
Internal dataset – results

RGB	xyz + color
MAT-RS	xyz + color + radii and separation angles
MAT-SP	xyz + color + spoke vectors
MAT-BIS	xyz + color + bisector angles

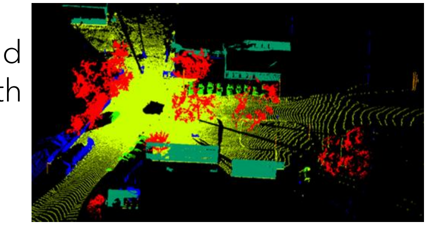
	RGB	MAT-RS		MAT-SP		MAT-BIS	
OA	0.84	0.89		0.87		0.84	
IoU							
Undefined	08.63%	09.71%	+1.08	13.94%	+5.31	09.22%	+0.59
Building	24.39%	54.49%	**+30.10**	43.22%	+18.83	38.64%	+14.25
Car	13.68%	22.22%	+8.54	28.05%	**+14.37**	22.25%	+8.57
Ground	88.10%	95.76%	+7.66	94.65%	+6.55	92.98%	+4.88
Pole	00.00%	00.00%		00.00%		00.00%	
Vegetation	73.85%	79.34%	+5.49	76.10%	+2.25	69.00%	-4.85

TU Delft cyclomedia

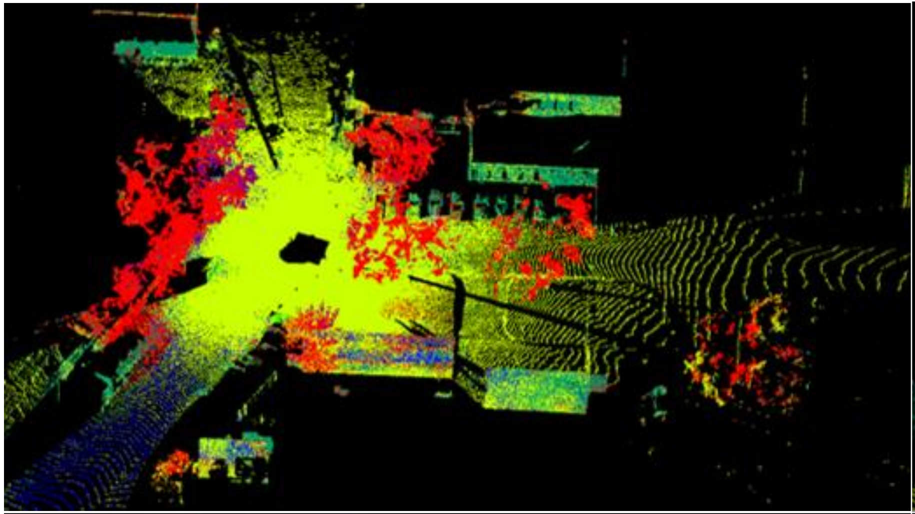
3D medial axis transform as a point feature

Internal dataset – results

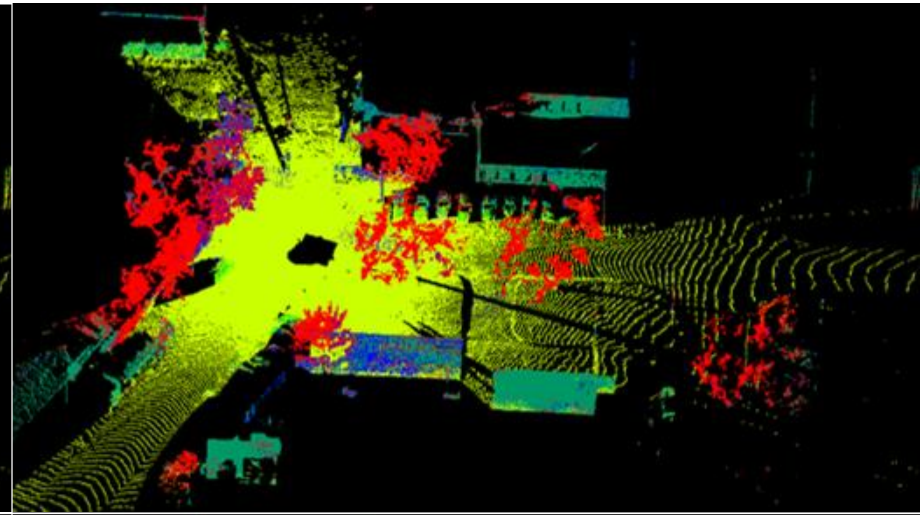
Ground truth

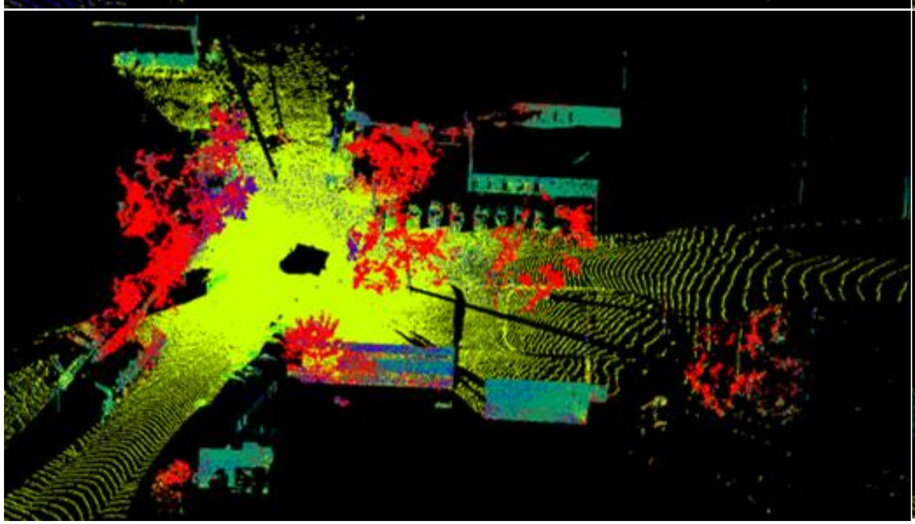


RGB classification point cloud

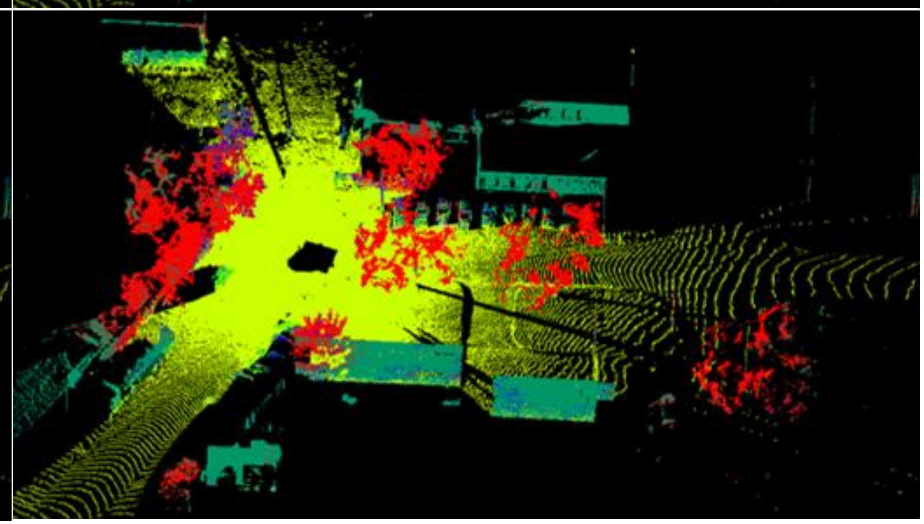


MAT spoke vectors classification point cloud





Bisector angles classification point cloud

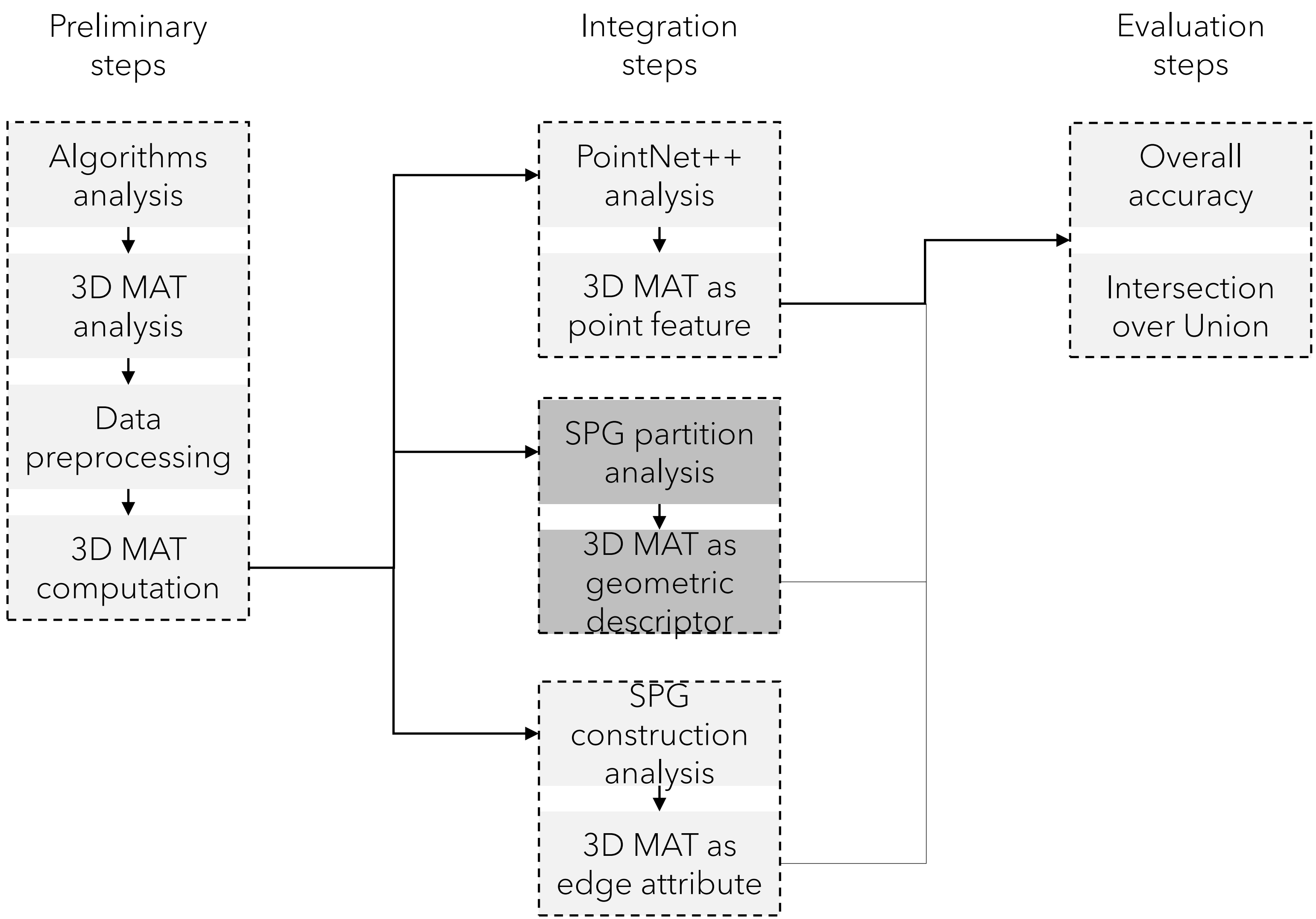


Radius and separation angle classification point cloud

Sum up

- Radius and separation angle improve the accuracy of the algorithm
- Both radius and separation angle contribute to the increase in accuracy
- MAT coordinates are prone to lead to overfitting and in general introduce ambiguity in the algorithm
- Even with real data, radius and separation angle introduce improvements in the accuracy of the algorithm
- The results can be improved for the internal dataset, if class weighting is applied

METHODOLOGY
Pipeline – integrated algorithm



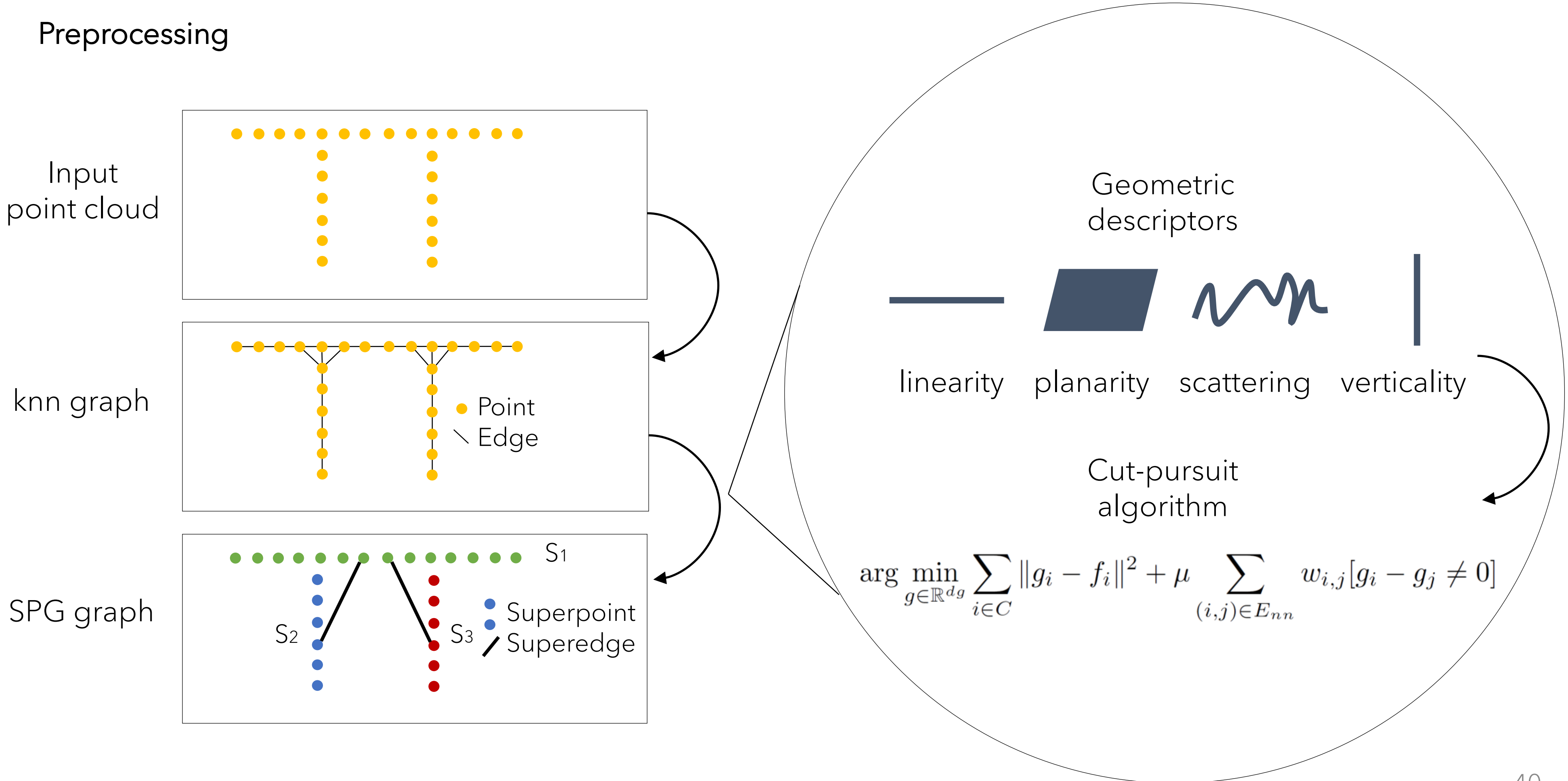
3D medial axis transform as a geometric descriptor

SPG partition analysis

Graph based networks

Superpoint Graph

Preprocessing



$$\arg\min_{g \in \mathbb{R}^{d_g}} \sum_{i \in C} \|g_i - f_i\|^2 + \mu \sum_{(i,j) \in E_{nn}} w_{i,j} [g_i - g_j \neq 0]$$

Graph based networks

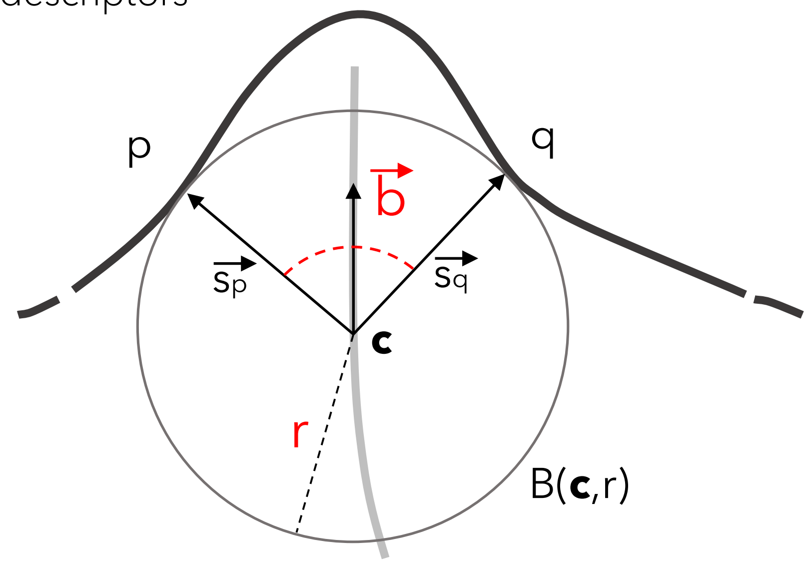
Superpoint Graph

Radii, separation angles and medial bisectors as geometric descriptors

r radius

separation angles

b medial bisector



Default geometric descriptors

linearity planarity scattering verticality

Goal: improve the partition of the point cloud in homogeneous shapes

Assumption: better partition leads to better overall results

Computed as a function of the Eigen values and vectors for a point's neighborhood

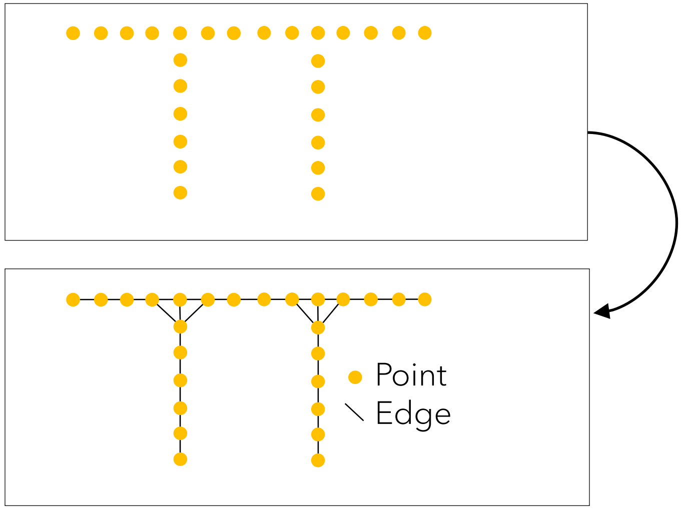
Graph based networks

Superpoint Graph

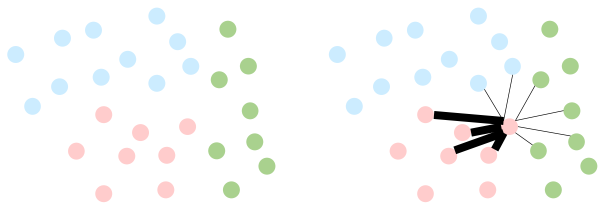
Knn graph: edge weight as inverse distance between point and neighbors

Input point cloud

knn graph



Knn graph: edge weight strengthened if point and neighbor belong to the same medial sheet



Goal: improve the partition of the point cloud in homogeneous shapes

Goal: increase similarity between SPG and structured MAT

Assumption: better partition leads to better overall results

Default	linearity + planarity + scattering + verticality
MAT	default + radii and separation angles (int, est)
Bisector	default + medial bisectors
Edge weight	default with different edge weight

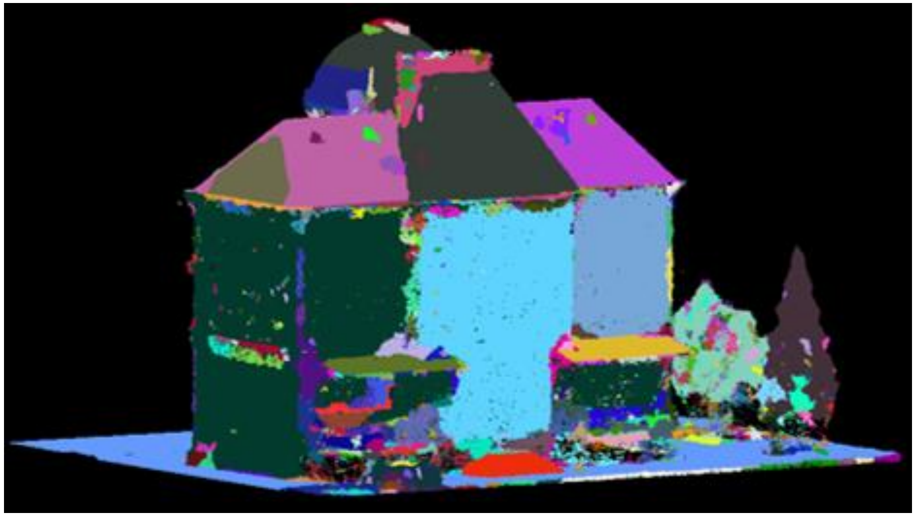
Cut-pursuit algorithm - number of parts

Point cloud	Default	MAT	Bisector	Edge weight
train1	642	1502	646*	595
train2	709	1620	844*	504
eval1	632	1831	670*	528
eval2	765	1757	997*	556
val1	1685	3511	2218*	1334

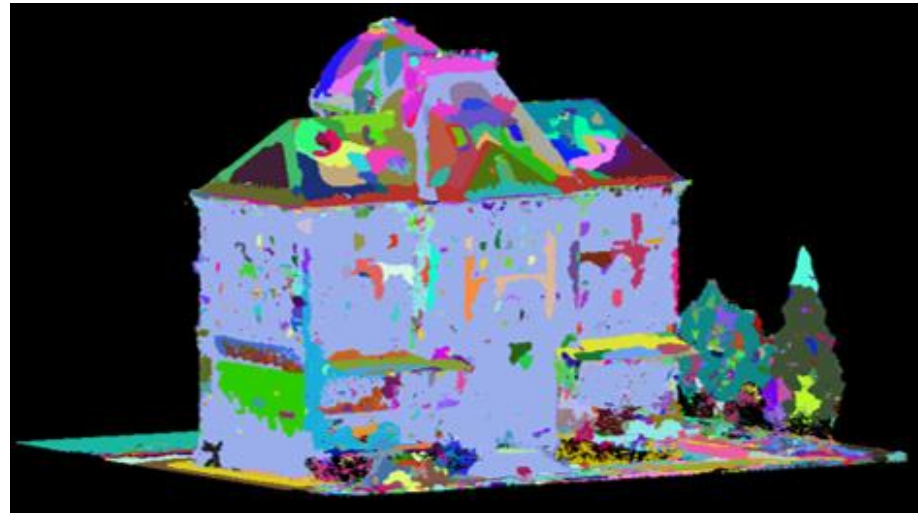
* Regularization strength parameter modified

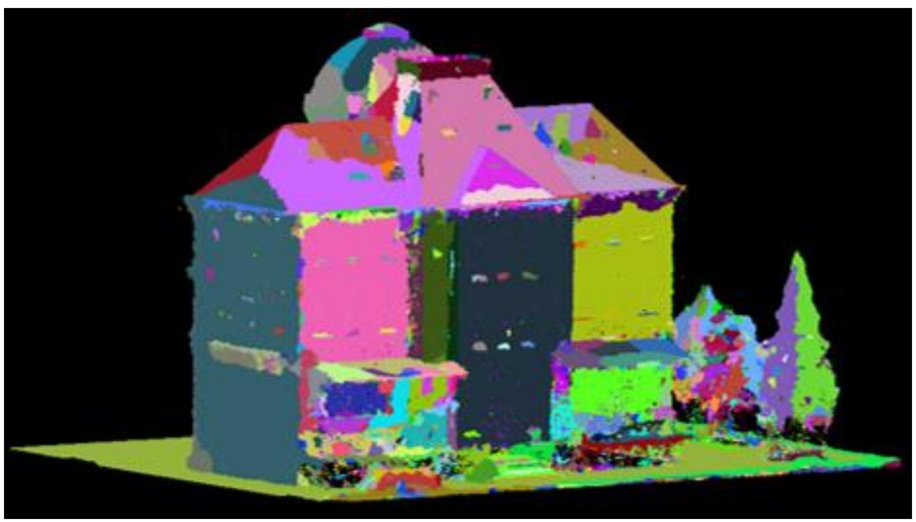
3D medial axis transform as a geometric descriptor
3DOM - results

3DOM point cloud – default partition



3DOM point cloud – MAT partition



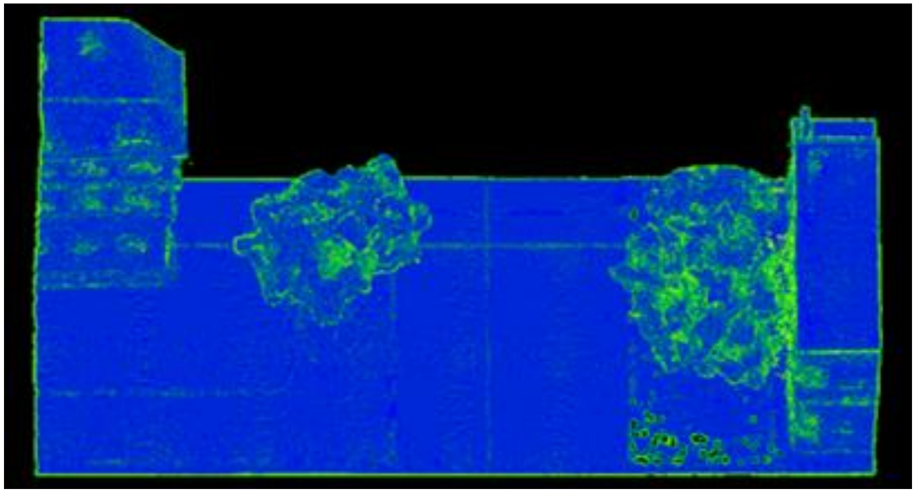


3DOM point cloud – medial bisector partition

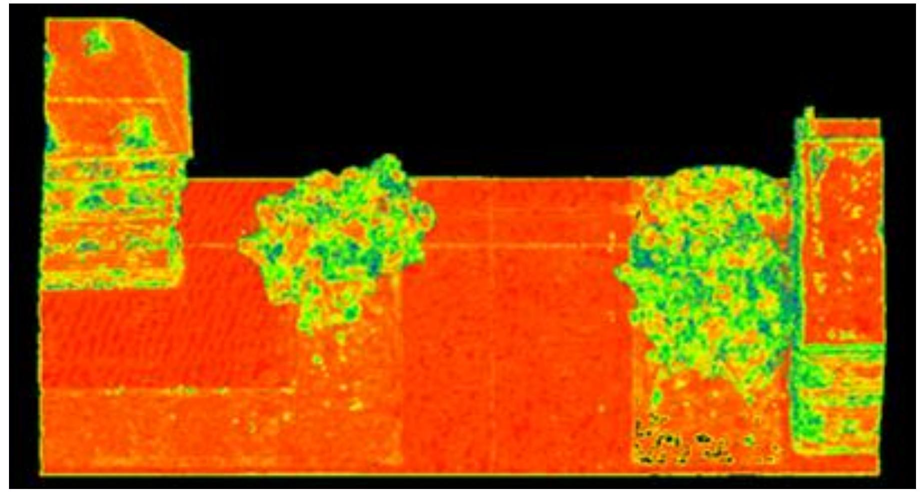
3DOM point cloud – edge weight partition

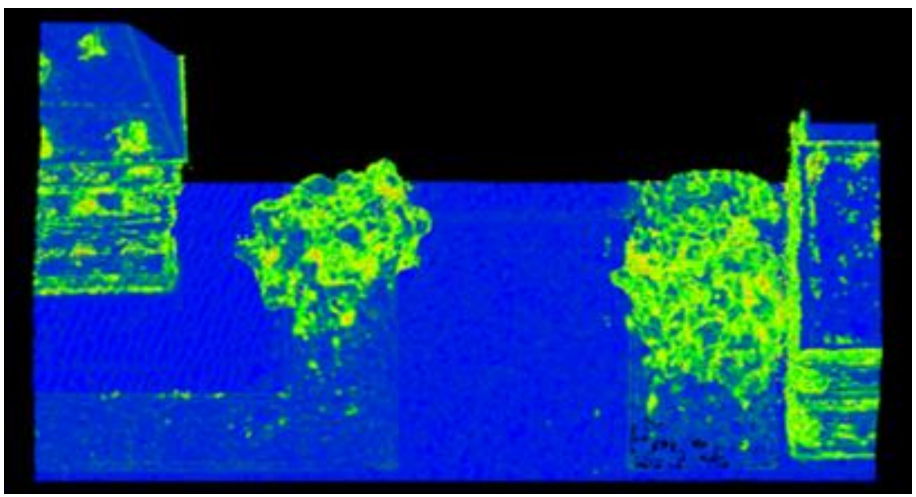
3D medial axis transform as a geometric descriptor
3DOM – analysis of results

3DOM point cloud – linearity

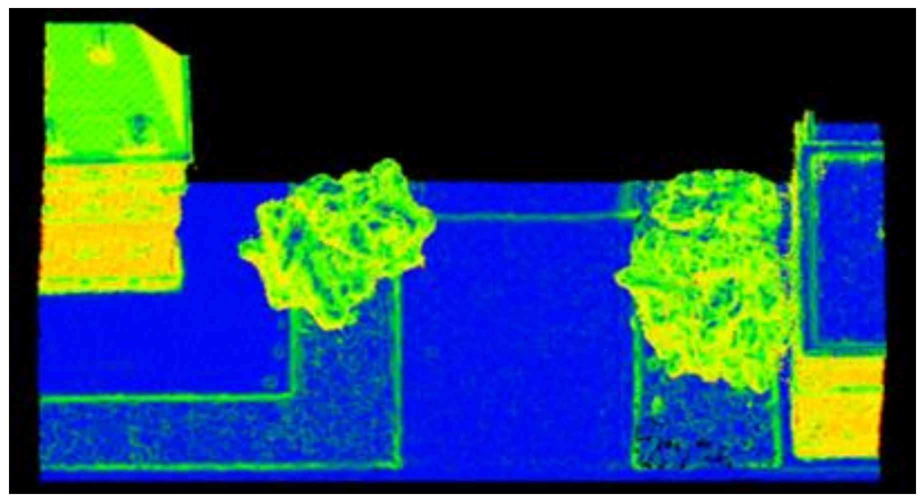


3DOM point cloud – planarity





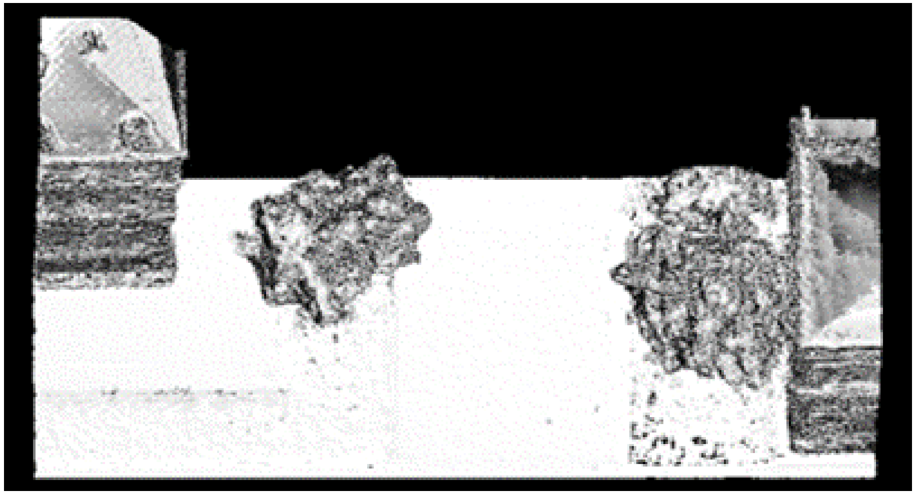
3DOM point cloud – scattering



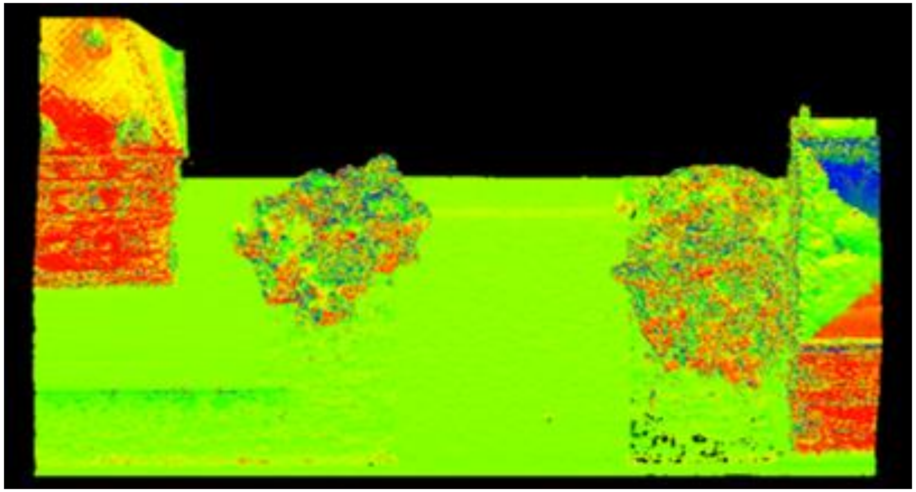
3DOM point cloud – verticality

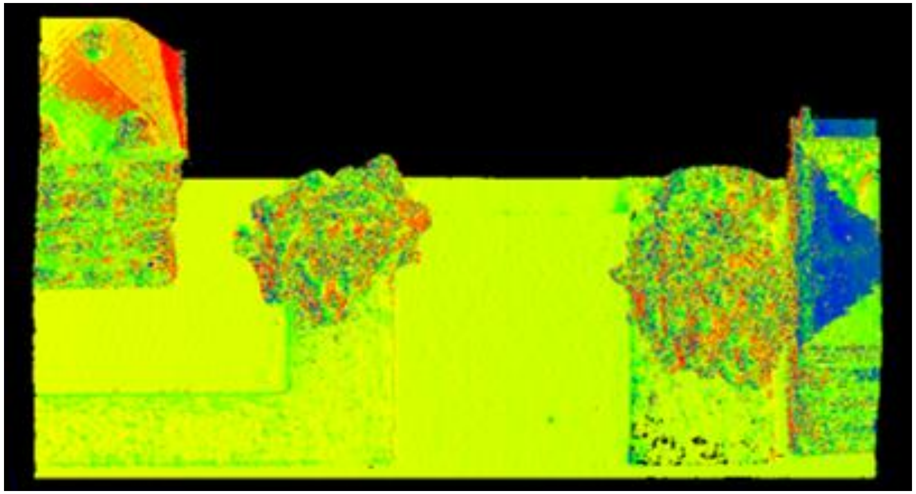
3D medial axis transform as a geometric descriptor
3DOM – analysis of results

3DOM point cloud – medial bisectors

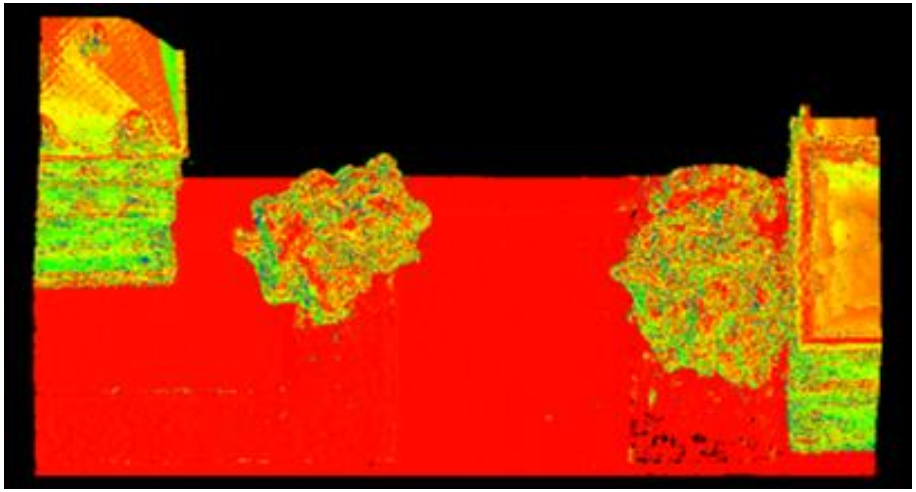


3DOM point cloud – bisector1





3DOM point cloud – bisector2

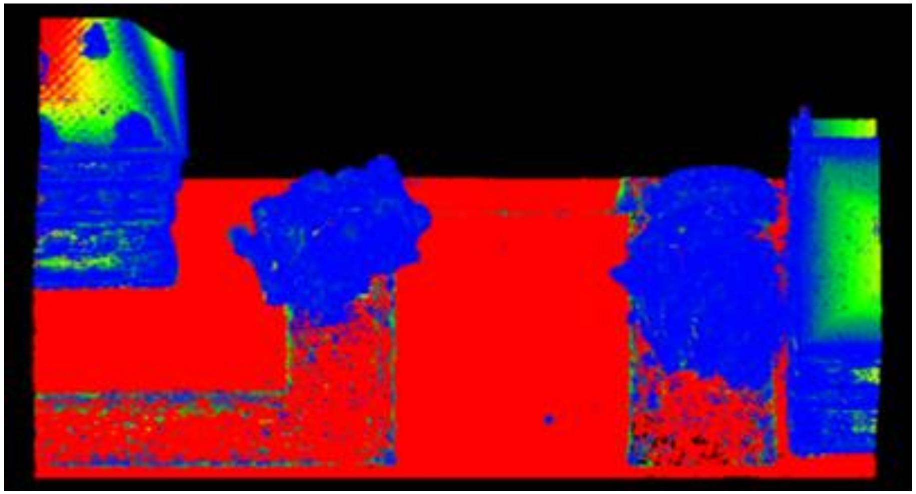


3DOM point cloud – bisector3

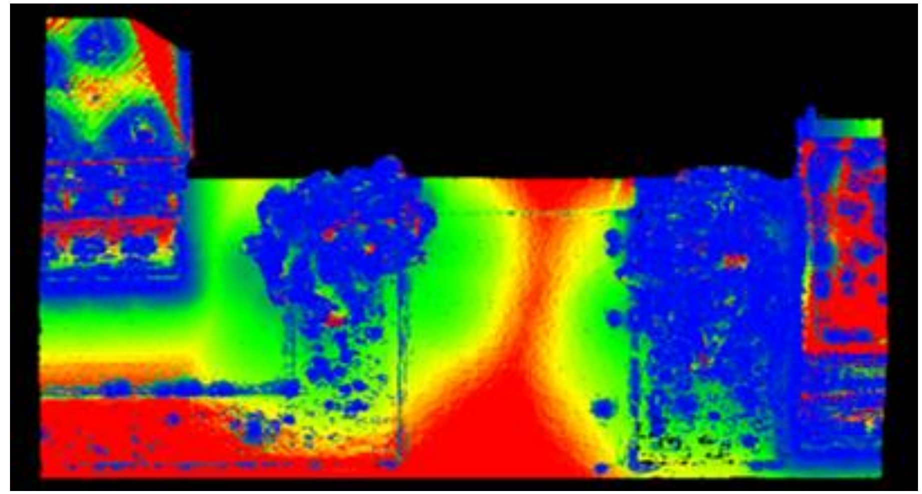
3D medial axis transform as a geometric descriptor

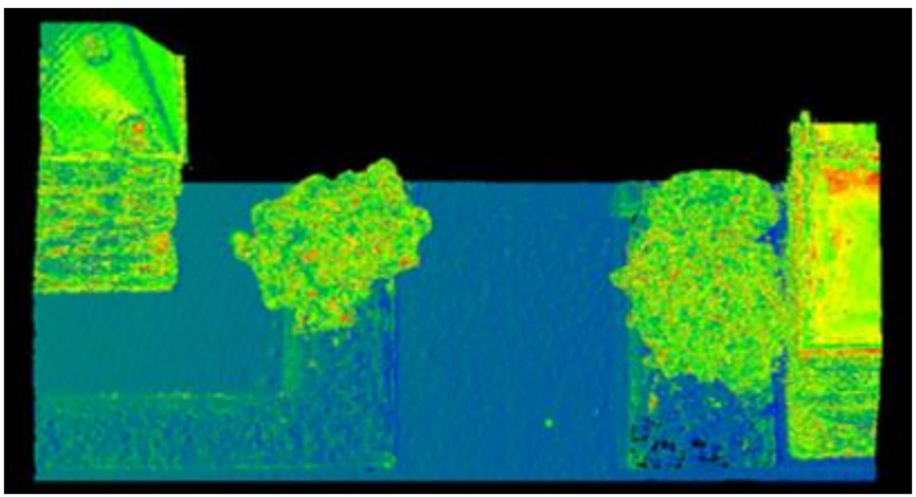
3DOM – analysis of results

3DOM point cloud – interior radius

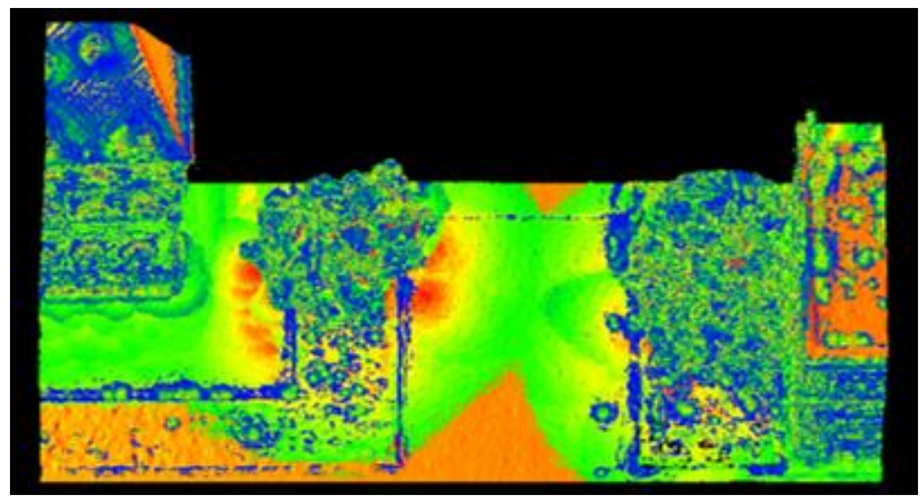


3DOM point cloud – exterior radius





3DOM point cloud – interior separation angle



3DOM point cloud – exterior separation angle

3D medial axis transform as a geometric descriptor
3DOM - results

Default	linearity + planarity + scattering + verticality
MAT	default + radii and separation angles (int, est)
Bisector	default + medial bisectors
Edge weight	default with different edge weight

	Default	MAT	Bisector	Edge weight
OA	74.36%	64.78%	67.25%	66.51%
IoU				
Ground	47.48%	30.89%	59.66%	55.01%
Grass	02.68%	43.67%	00.02%	19.27%
Shrub	28.89%	01.55%	57.51%	36.70%
Tree	66.78%	66.46%	64.13%	52.09%
Facade	79.01%	28.24%	67.64%	63.25%
Roof	51.74%	21.54%	03.08%	00.04%

3D medial axis transform as a geometric descriptor

SynthCity - results

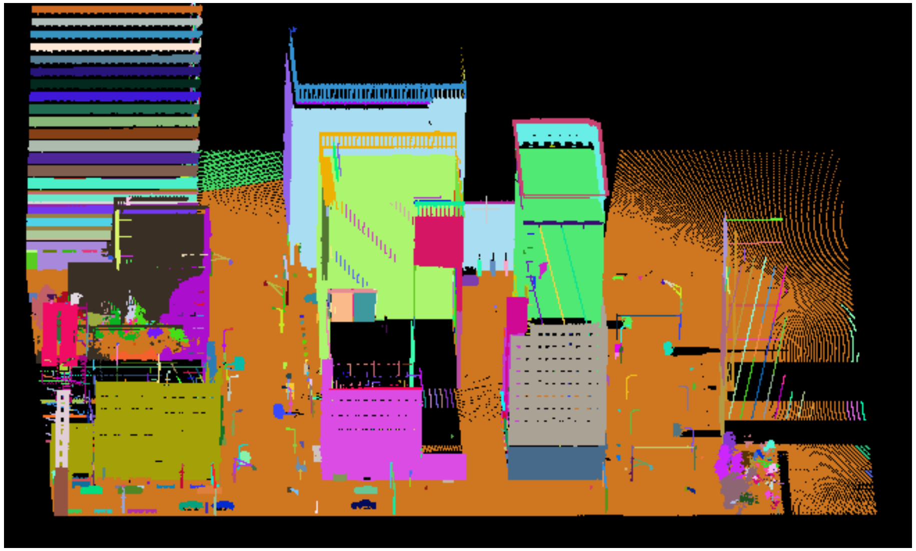
Default	linearity + planarity + scattering + verticality
MAT	default + radii and separation angles (int, est)
Bisector	default + medial bisectors
Edge weight	default with different edge weight

Cut-pursuit algorithm - number of parts

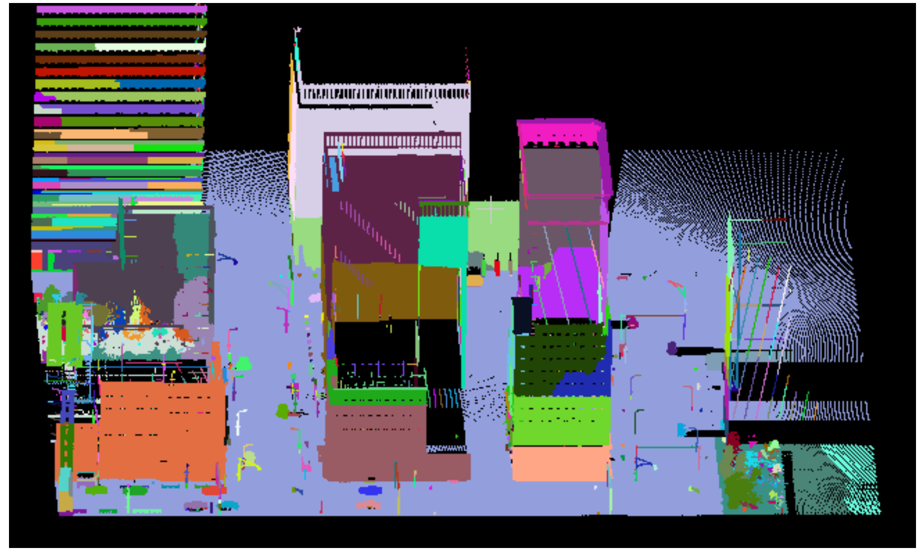
Point cloud	Default	MAT	Bisector	Edge weight
area1	656	755	1575	701
area2	840	991	2176	981
area3	770	1017	1735	896
area4	832	875	2001	912
area5	1064	1212	2661	1172
area6	886	1202	3053	969
area7	501	493	472	499
area8	472	382	684	525
area9	557	780	1220	639

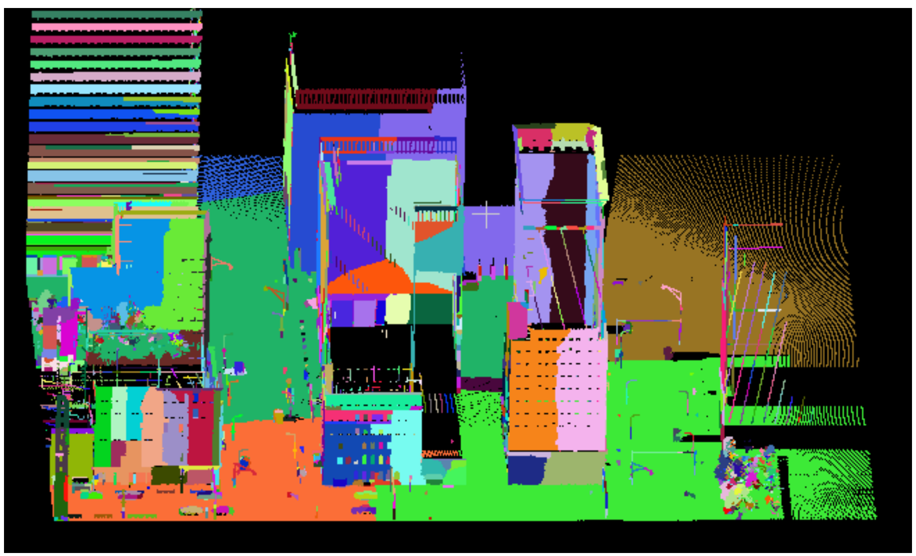
3D medial axis transform as a geometric descriptor
SynthCity - results

SynthCity point cloud – default partition

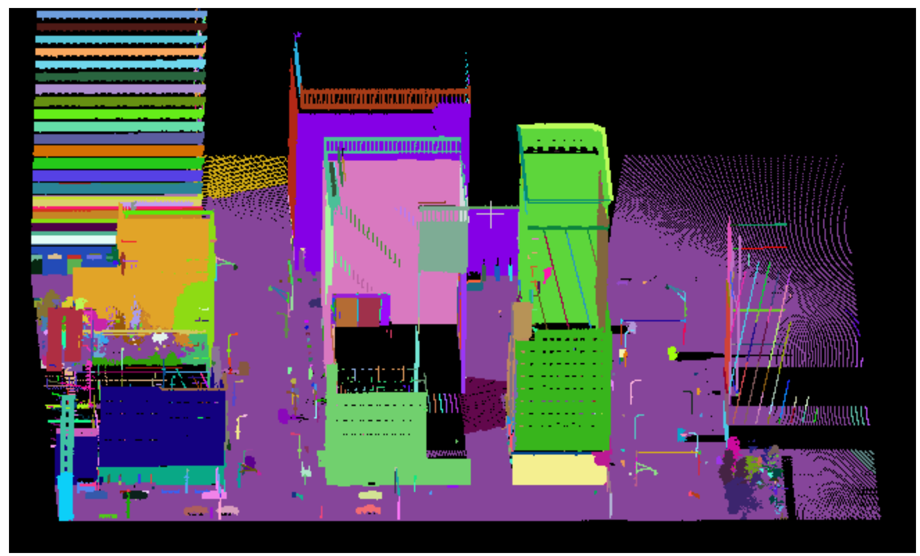


SynthCity point cloud – MAT partition





SynthCity point cloud – medial bisector partition



SynthCity point cloud – edge weight partition

3D medial axis transform as a geometric descriptor

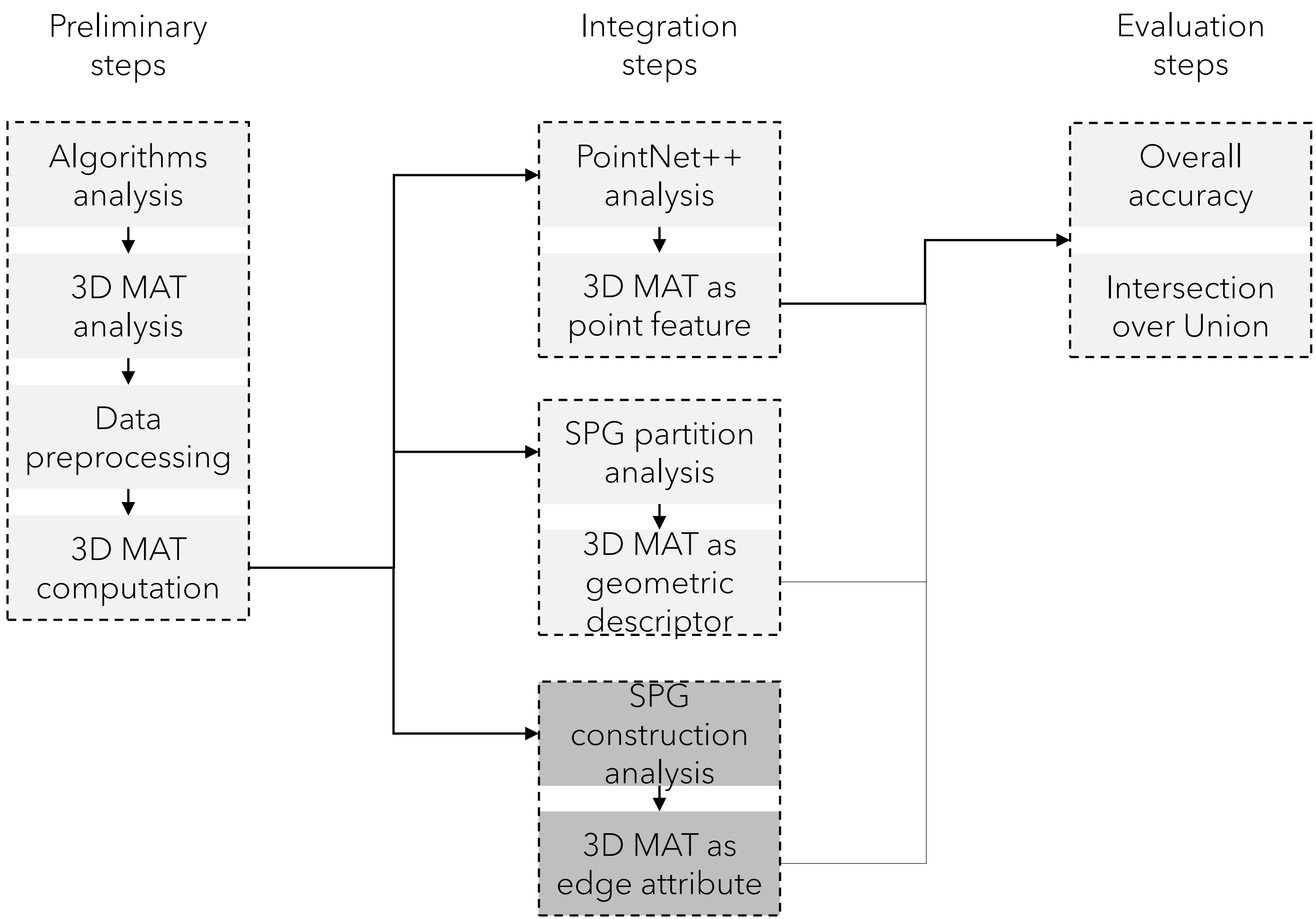
SynthCity - results

Default	linearity + planarity + scattering + verticality
MAT	default + radii and separation angles (int, est)
Bisector	default + medial bisectors
Edge weight	default with different edge weight

	Default	MAT	Bisector	Edge weight
OA	89.04%	85.28%	85.84%	80.71%
IoU				
Building	97.75%	96.36%	92.14%	94.81%
Car	66.37%	56.16%	42.47%	38.17%
Natural ground	00.20%	44.38%	01.83%	01.46%
Ground	06.76%	12.20%	11.39%	03.90%
Pole-like	42.52%	48.16%	01.04%	24.77%
Road	41.53%	46.56%	00.00%	41.52%
Street furniture	29.59%	15.87%	00.00%	18.20%
Tree	98.34%	96.69%	66.00%	94.80%
Pavement	00.04%	00.00%	00.00%	00.00%

METHODOLOGY

Pipeline – integrated algorithm

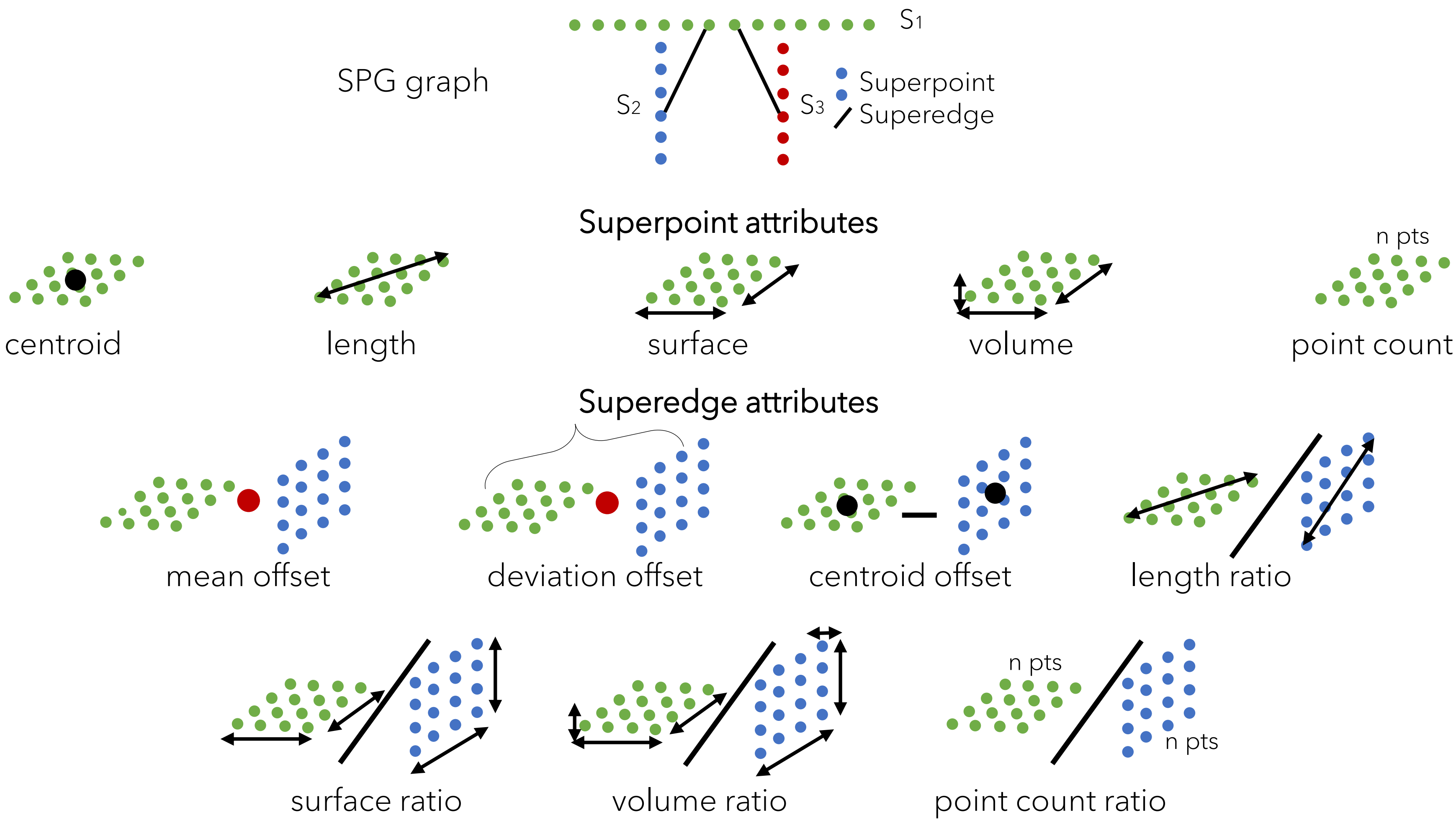


3D medial axis transform as an edge attribute

SPG construction analysis

Graph based networks

Superpoint Graph



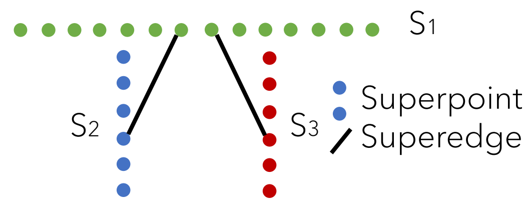
3D medial axis transform as an edge attribute

3D MAT use

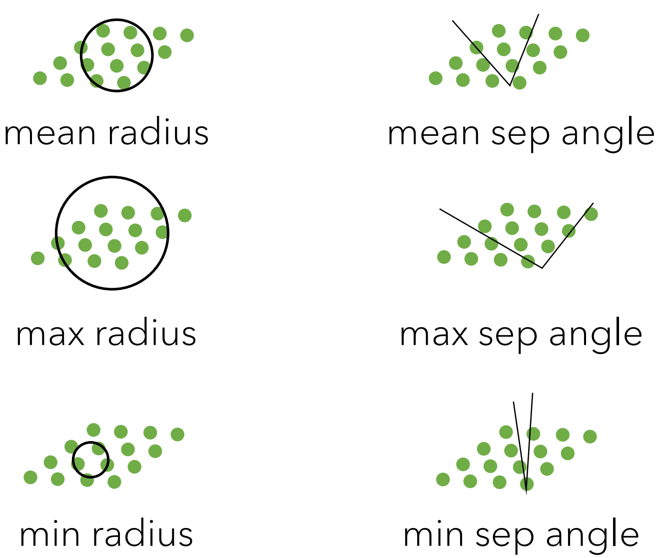
Graph based networks

Superpoint Graph

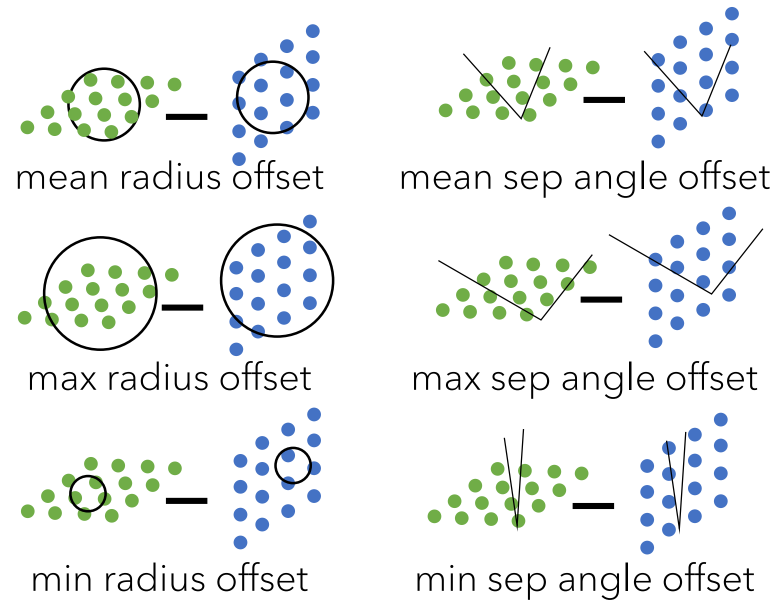
SPG graph



Superpoint attributes



Superedge attributes



3D medial axis transform as an edge attribute
3DOM - results

Default	SPG graph edge attributes
Mean	mean radii and separation angles (int, est)
Min-max	min and max radii and separation angles (int,est)

	Default	Default + Mean	Mean	Default	Default + Min-max	Min-max
OA	74.36%	70.12%	74.04%	72.64%	73.64%	72.77%
IoU						
Ground	47.48%	35.70%	29.40%	71.68%	53.63%	23.87%
Grass	02.68%	20.97%	15.62%	00.11%	00.00%	00.08%
Shrub	28.89%	60.32%	22.53%	05.62%	18.99%	37.53%
Tree	66.78%	69.54%	70.86%	50.05%	47.52%	62.47%
Façade	79.01%	43.78%	27.53%	69.48%	72.18%	33.28%
Roof	51.74%	10.23%	62.69%	01.09%	28.69%	00.00%

Sum up

- Introducing MAT information to partition a point cloud leads to different results in different datasets
- For the 3DOM dataset:
  - The number of parts is highly increased using radii, separation angles and medial bisectors
  - The number of parts is decreased when modifying the edge weight
- For the SynthCity dataset:
  - The number of parts is similar using radii, separation angles and medial bisectors
  - The number of parts is increased when modifying the edge weight
- In general, the default partition leads to better overall results
- Using the MAT to enrich the SPG edges' attributes does not lead to improvements, the reason is that the structured MAT is not like the SPG in practice

3D MAT

✓

- to give context to points	local geometry of the medial atom
- most useful properties	radii and separation angles
- to improve the accuracy of existing deep learning methods	yes
- real data-set vs synthetic data-set	similar trends in the results

✗

- to partition a point cloud	not useful in the cut-pursuit algorithm
- to enrich the SPG's edge information	not useful if SPG and MAT are not similar

How can the properties of the 3D medial axis transform be exploited in deep learning algorithms for point cloud semantic segmentation?

Radii, separation angles, spoke vectors and bisector angles can be successfully used as a *point feature* in a *point based* deep learning network

FUTURE WORK
& REFLECTIONS

General directions

Automatic computation of the 3D MAT

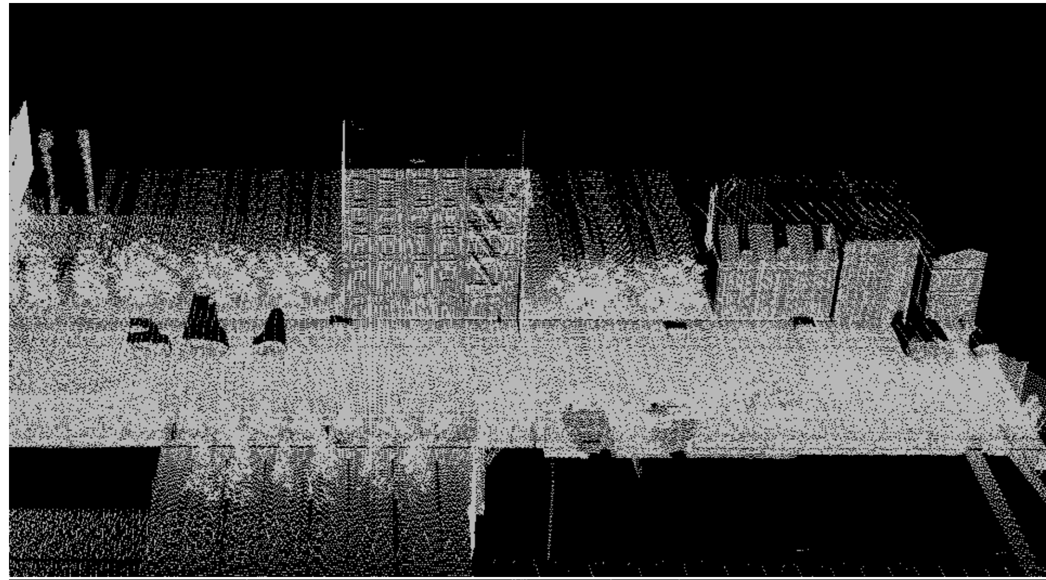
Analysis of different types of datasets

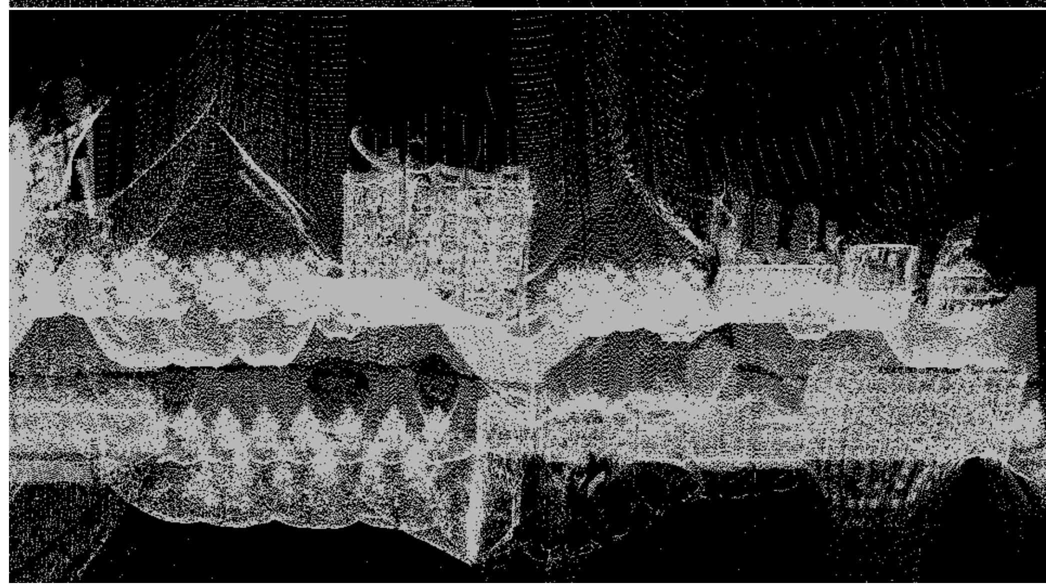
Superpoint graph

Use of 3D MAT adjacencies as SPG

Direct use of 3D MAT point cloud

SynthCity





SynthCity – MAT

THANK YOU!