



Semantic Representations on Satellite Images

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Project: Large Scale Semantic Perception on Sattelite Imagery



SAAB

VRICON

Goal: Automatically augment satellite imagery with annotations about objects, functions, and relations to enable 1) users to query the map 2) improve the recognition of objects and entities

Data



- 3D maps:
 - Formats: Ortho + DSM (GeoTIFF) and Collada.
 - Boden, Stockholm, part of Örebro (Collada only).
 - Multiple color bands to extract different features.
 - Resolution: 0.5m/px in all dimensions.
 - UTM coordinates, WGS84, ellipsoid.

Ortho + DSM

- Multiband + Synthetic Bands

- Ortho – aerial images are combined to remove projection tilts and displacements.

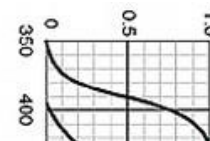
- DSM – surface model – per-pixel mapped to Ortho, elevation includes buildings and trees.

- GeoTiff



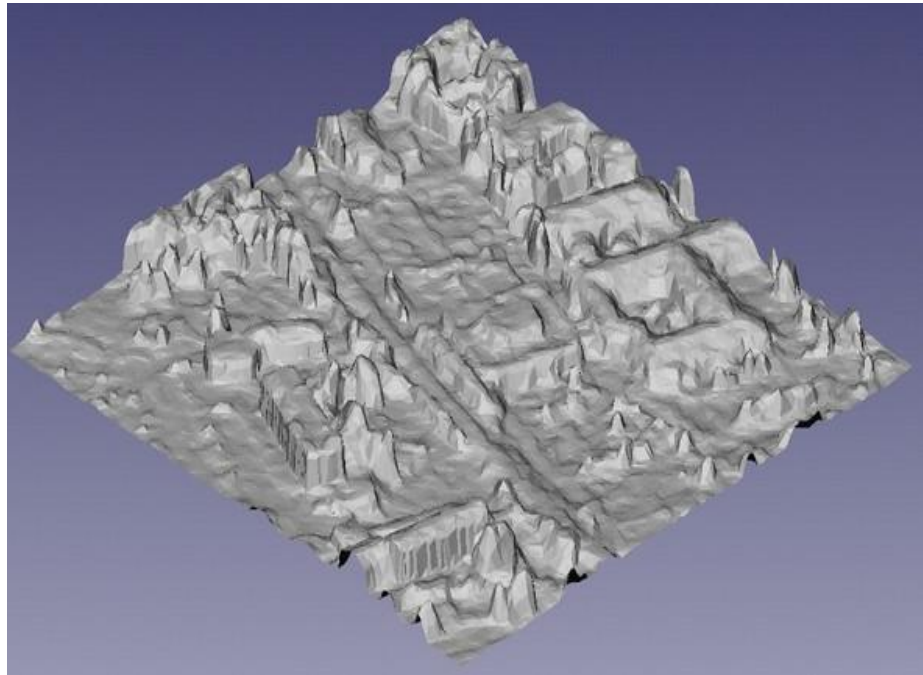
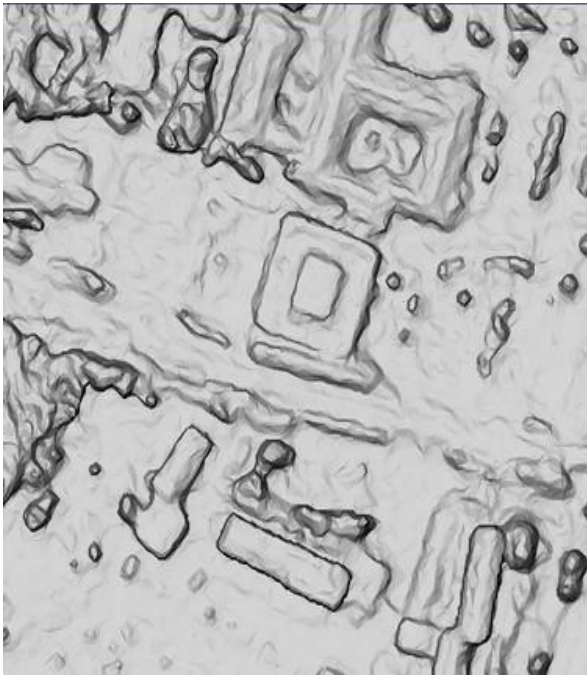
Raw Bands

- Panchromatic [450-800] – blend of visible light into a grayscale;
- Coastal [400-450] – violet and deep blue, useful primarily for shallow waters, aerosols, dust, smoke;
- Blue [450-510] – useful for soil/vegetation discrimination, forest type mapping, and identifying man-made features;
- Green [510-580] – helps find oil on the surface of water, and vegetation (plant life); reflects more green light than any other visible color; man-made features are still visible;
- Yellow [585-625] – soils, sick foliage, hardwood, larch foliage (autumn);
- Red [630-690] - useful for identifying vegetation types, soils, and urban (city and town) features;
- Red Edge [705-745] – where the reflectance of vegetation changes rapidly;
- NIR1 [770-895] – used to measure plant health, good for mapping shorelines and biomass content; very good at detecting and analyzing vegetation;
- NIR2 [860-1040] – similar to NIR1
- + sharpened RGB



Collada

- Projected 3D mesh + textures.
- 13 levels of details, a lot of data, quadtree arrangement.

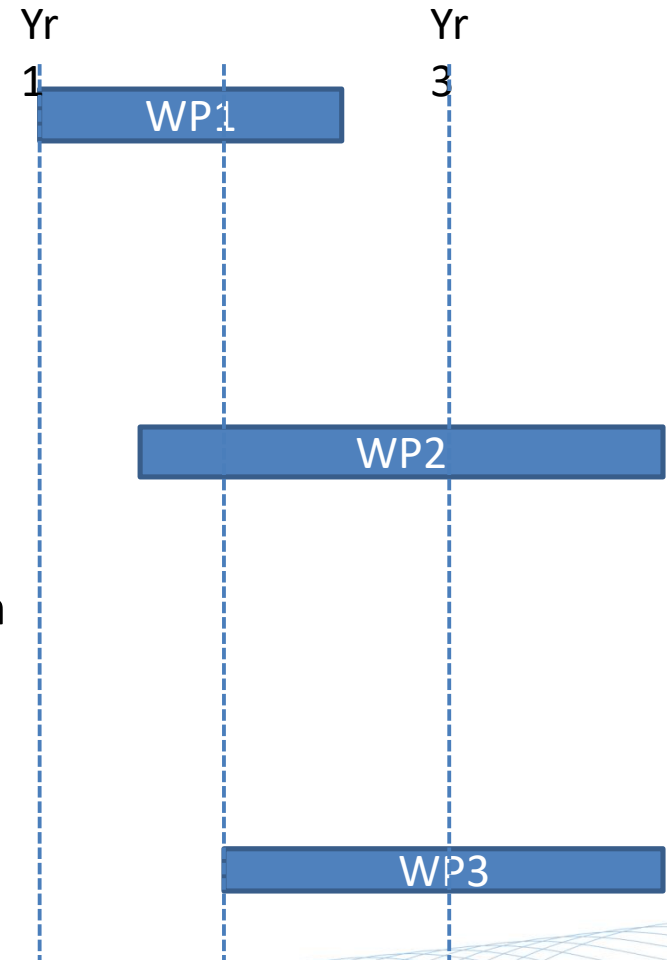


Project Workpackages

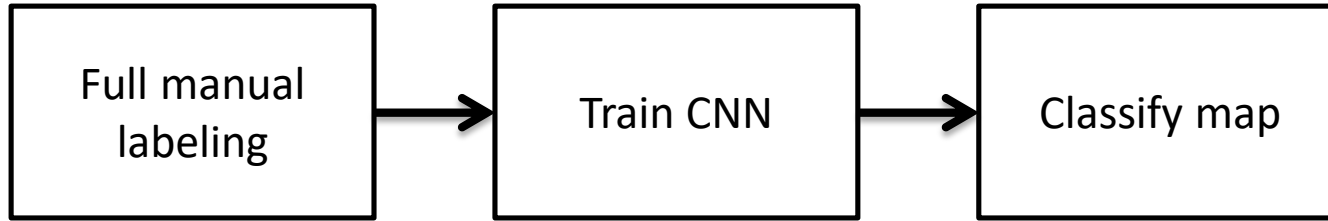
WP1 SEGMENT & CLASSIFY: segmentation and classification of 3D airborne map data

WP2 ANNOTATE & ANCHOR: segment regions in the map for classification and categorize the segments into fixed semantic categories.

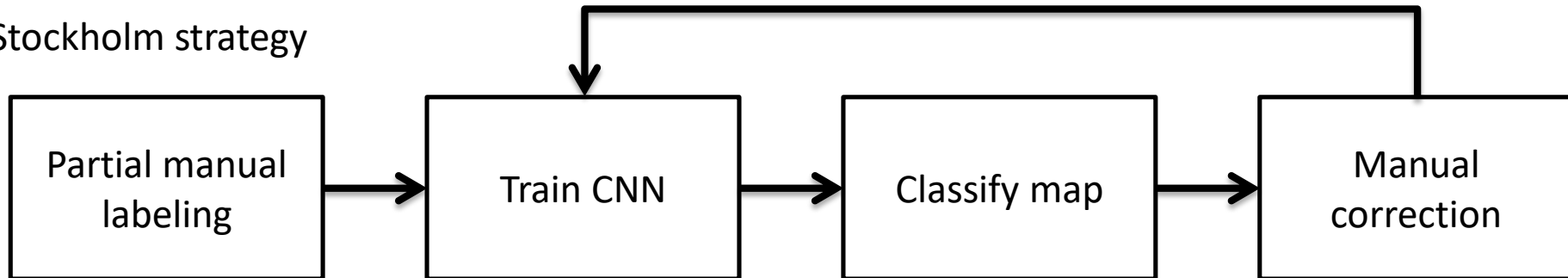
WP3 REASON & QUERY: a search engine which is composed of a reasoner and a query mechanisms



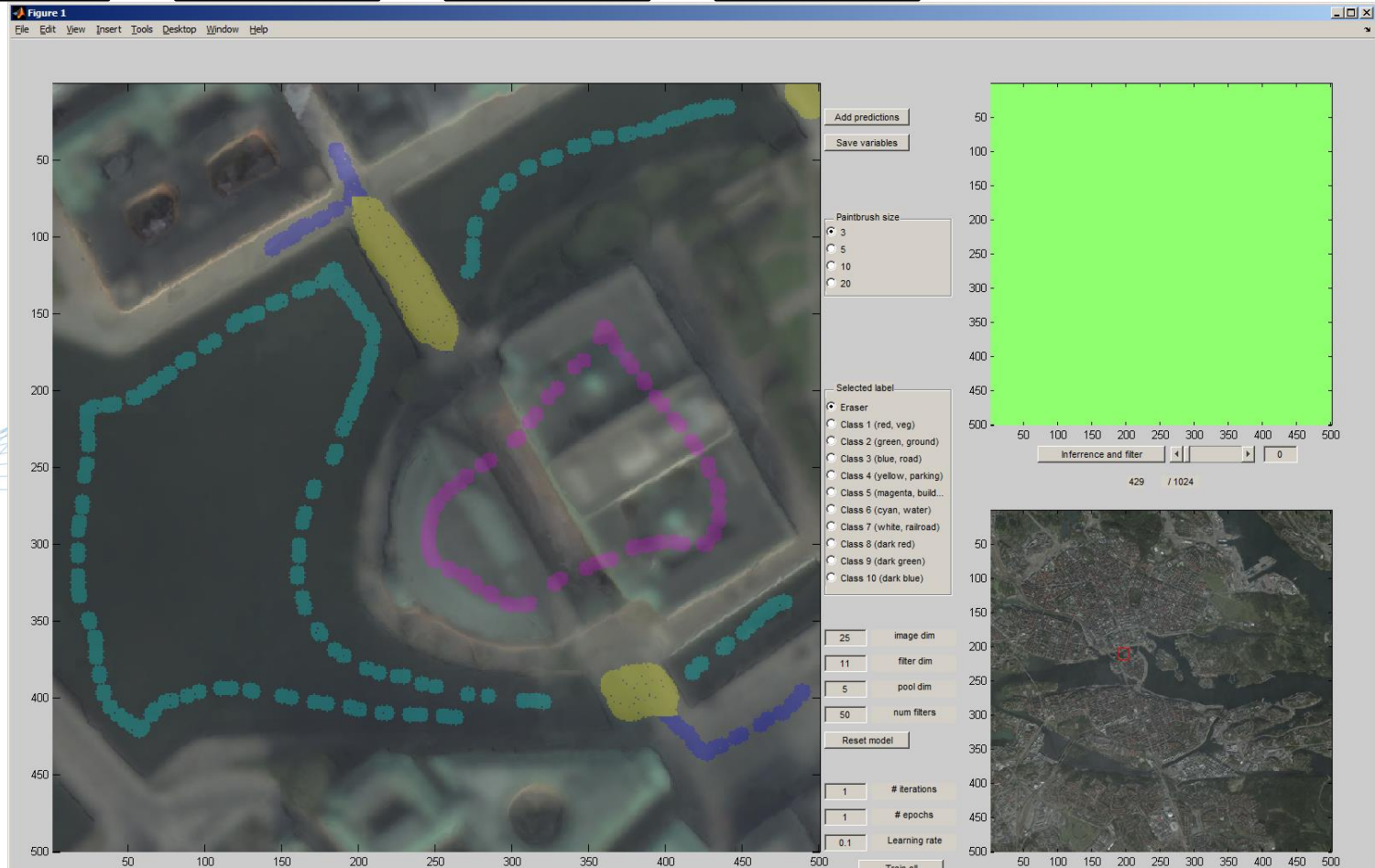
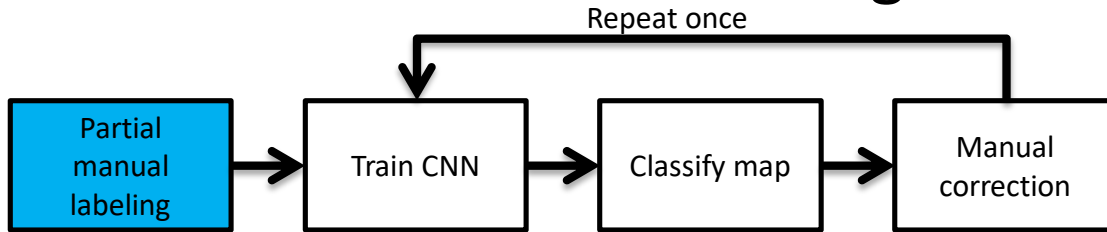
Traditional strategy



Stockholm strategy

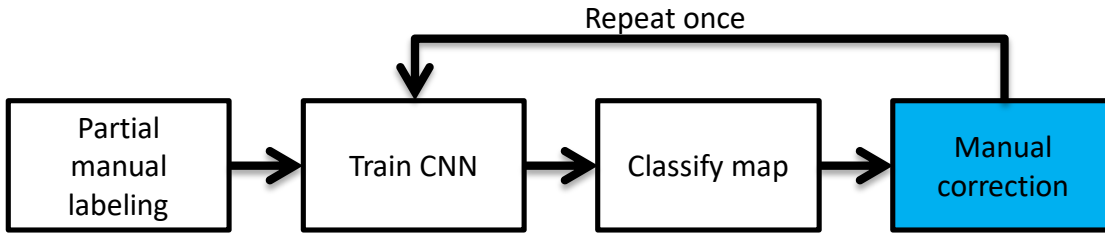


GUI for labeling and training

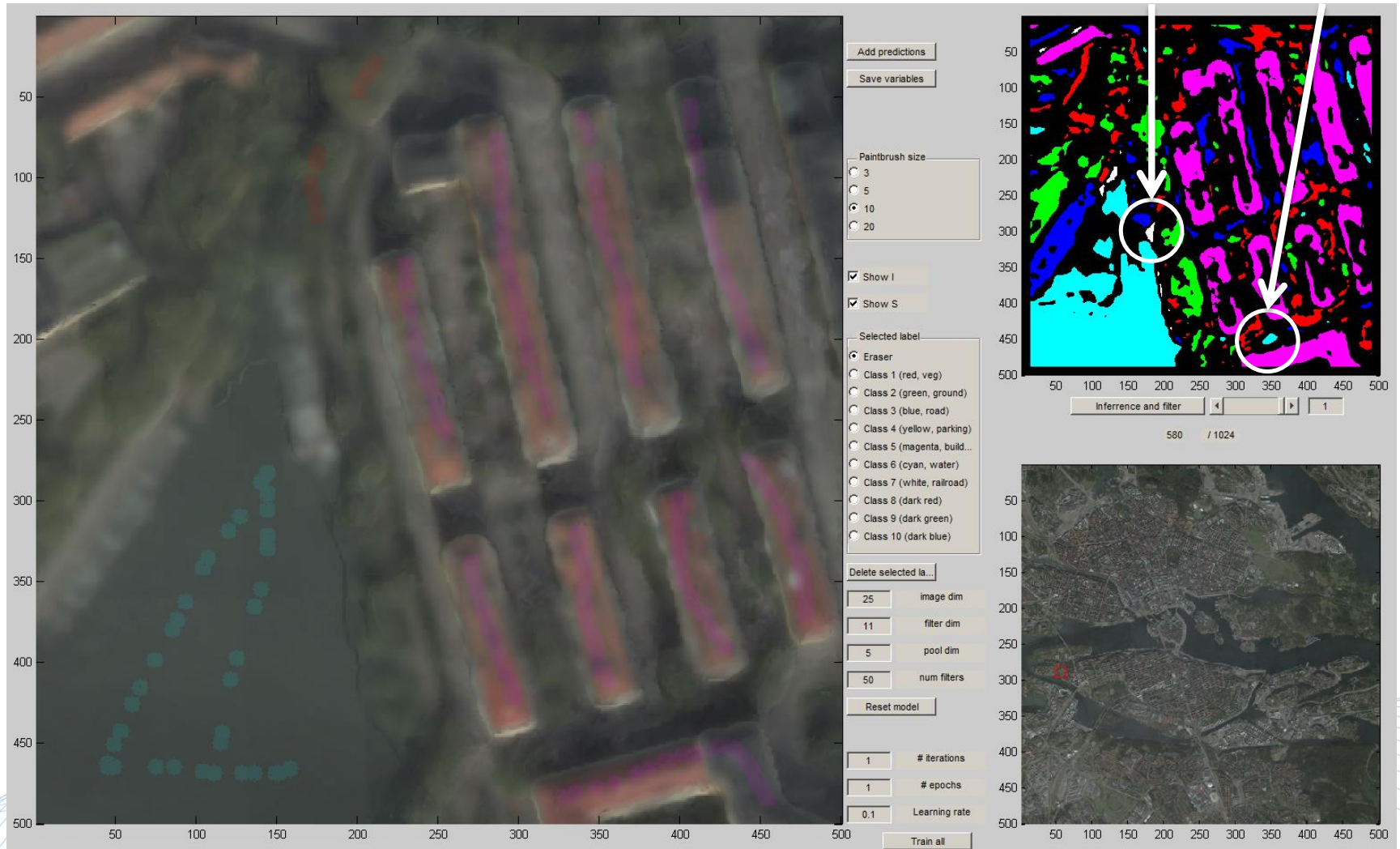


7 classes. *Parking* replaced by *bridge*.

Manual correction



Railroad? Water?

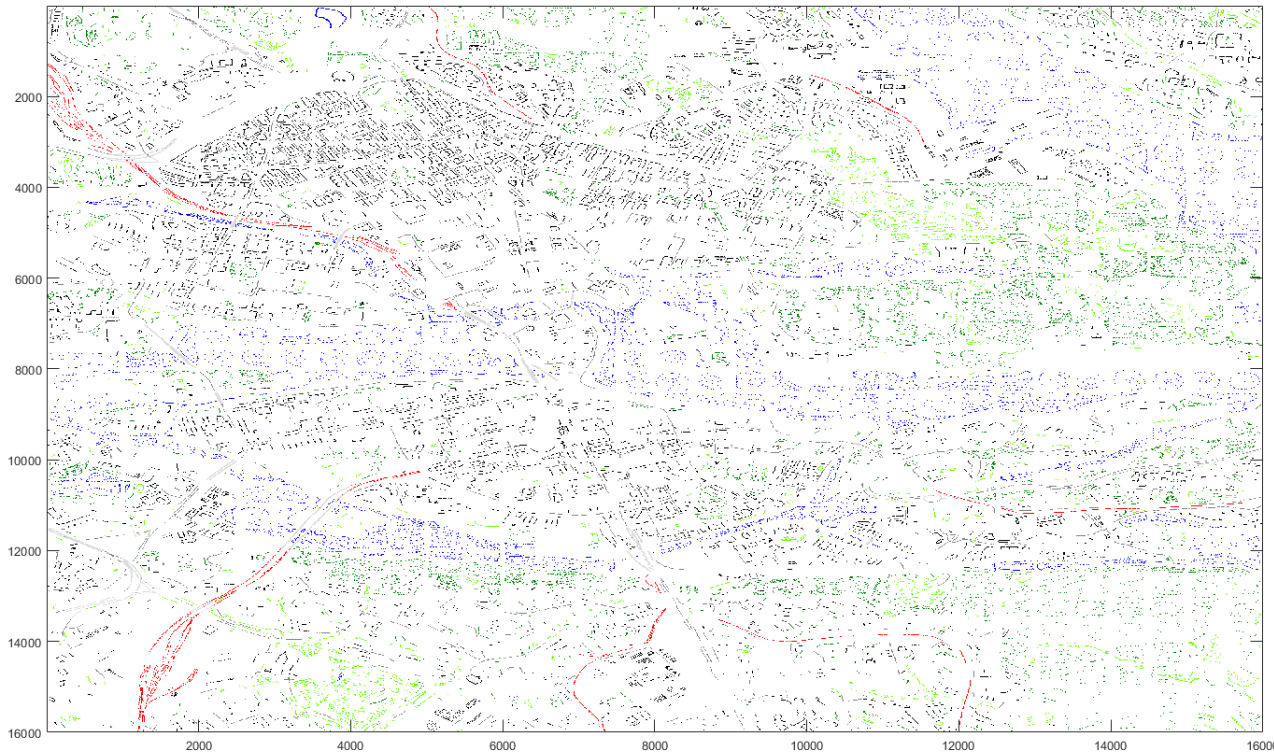


The screenshot shows a software interface for manual correction. On the left is a grayscale aerial image with a red bounding box. On the right is a color-coded classification map of the same area. Two white circles on the map are pointed to by arrows labeled 'Railroad?' and 'Water?'. The interface includes a control panel with the following settings:

- Buttons: Add predictions, Save variables
- Paintbrush size: 3, 5, 10, 20
- Show I: Show I, Show S
- Selected label: Eraser
- Class 1 (red, veg), Class 2 (green, ground), Class 3 (blue, road), Class 4 (yellow, parking), Class 5 (magenta, build...), Class 6 (cyan, water), Class 7 (white, railroad), Class 8 (dark red), Class 9 (dark green), Class 10 (dark blue)
- Delete selected la...
- 25 image dim, 11 filter dim, 5 pool dim, 50 num filters
- Reset model
- 1 # iterations, 1 # epochs, 0.1 Learning rate
- Train all

At the bottom right, there is an 'Inference and filter' section with a slider set to 1 and a count of 580 / 1024. Below the map is a zoomed-in view of the red bounding box area.

Manually labeled groundtruth



Unlabeled	94.7%
Vegetation	1.1%
Ground	0.5%
Road	0.8%
Bridge	0.2%
Building	1.9%
Water	0.7%
Railroad	0.2%

5.3 % of map labeled in 6 hours. (100% would have taken >120 hours)

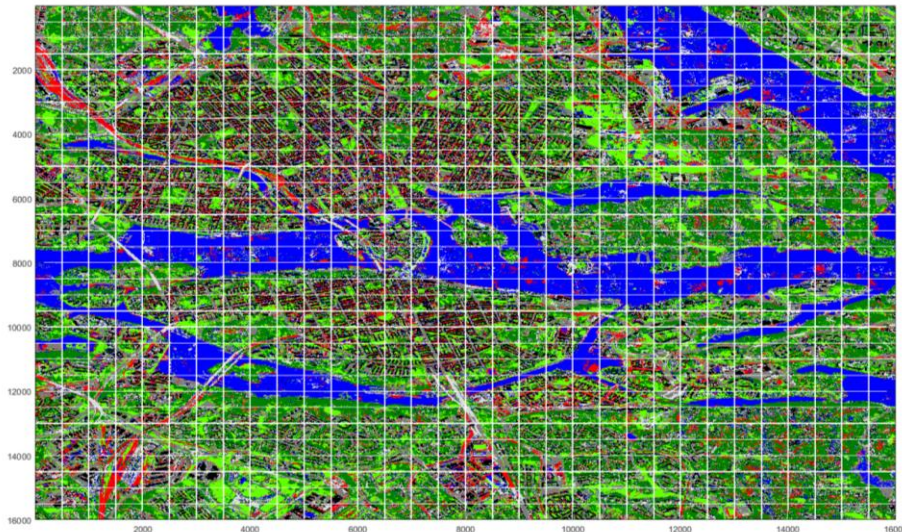
Classification result

- Trained on 90% initial manual labeled groundtruth
- Tested on 1000 randomly drawn pixels per class from the remaining 10 %

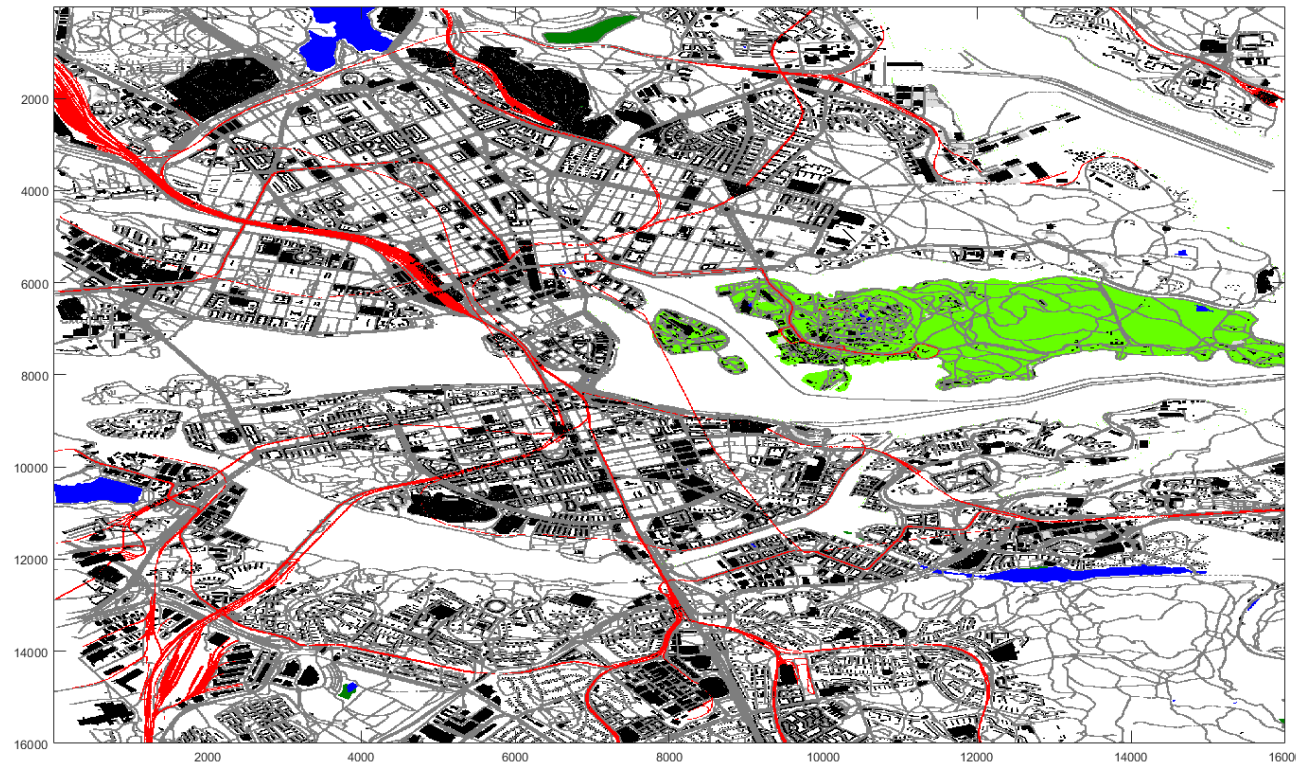
Equal class distribution in training data

95.6	1.1	0.3	1.4	0.3	0.9	2.9
1.2	95.0	0.6	0.7	0.1	0.8	1.7
0.2	1.3	94.1	3.4	0.1	0.4	3.8
0.7	0.7	1.9	78.7	7.2	2.4	3.6
0.2	0.1	0.1	9.2	91.0	0.4	0.9
0.5	0.7	0.5	2.7	0.6	93.3	2.4
1.5	1.1	2.5	3.8	0.6	1.9	84.7

Overall accuracy: 90.34%



OSM groundtruth



Unlabeled	52.4%
Vegetation	0.1%
Ground	2.8%
Road	28.6%
Parking	0.4%
Building	12.1%
Water	0.8%
Railroad	2.8%

Roads and buildings are well labeled, but not the other classes

Lantmäteriet groundtruth



Unlabeled	17.8 %
Vegetation	11.4 %
Ground	15.4 %
Road	22.4 %
Bridge	0.0 %
Building	13.8 %
Water	17.0 %
Railroad	2.23 %

All classes well labeled, except bridge

Using **on-line** sources of geo-data

(I) Using **on-line** sources of geo-data:

▣ **Läntmateriet** (vector-based representation of geo-related features)



- Water (32)
- Road (8202)
- RailRoad (634)
- Building (20094)
- Industry
- Residential
- School
- Hospital
- Police Station
- Train Station
- City Hall
- Sport Hall
- Fire Station
- University
- ...

▣ **Läntmateriet** (vector-based representation of geo-related features)

→ Transforming the **vector-based** representation into a **raster-based** representation

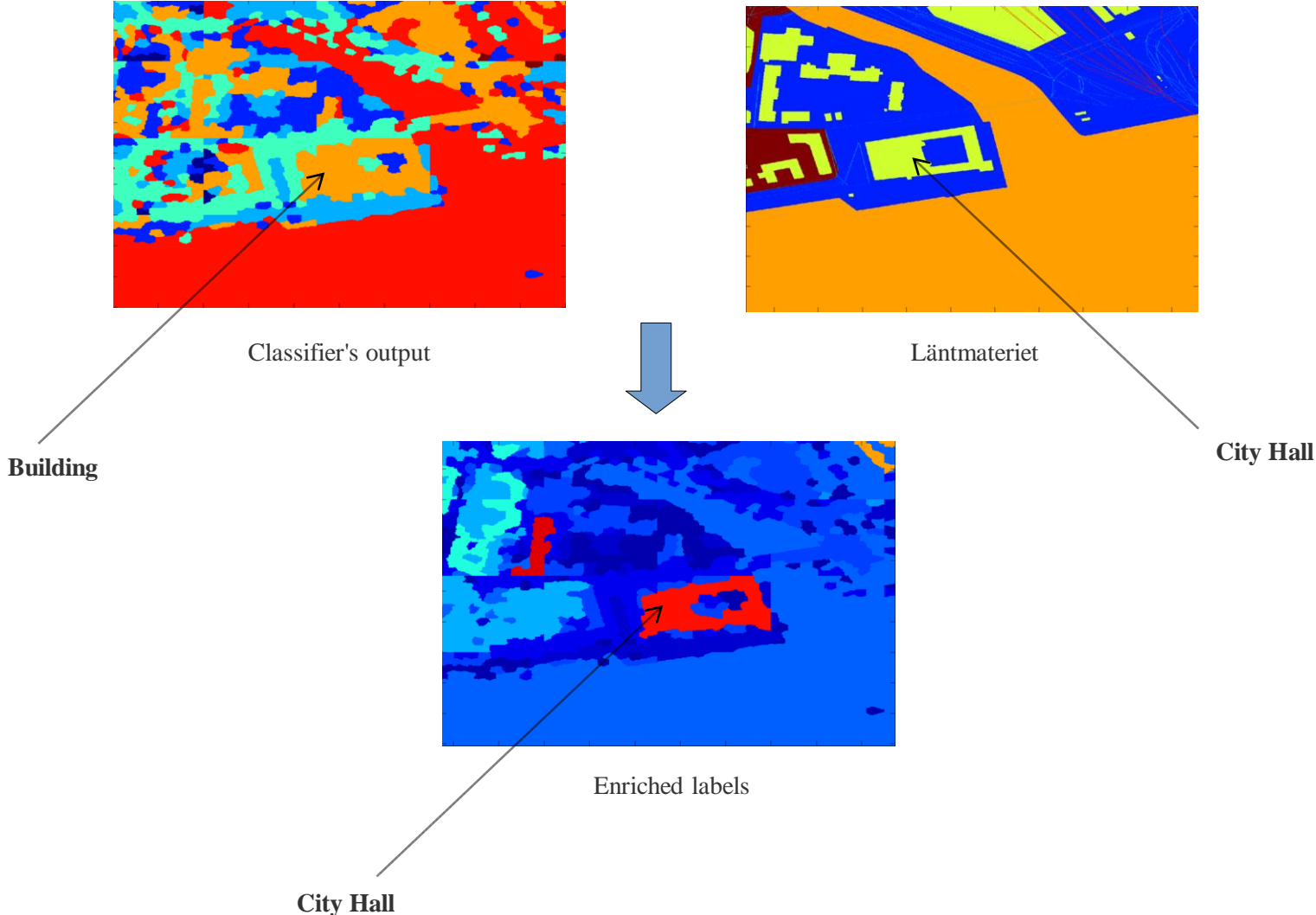


→ *Published in **GIScience 2016** - Workshop on Spatial Data on the Web*

(I) Using **on-line** sources of geo-data:



□ **Merging Lantmateriet with the Classifier output (focusing on buildings)**



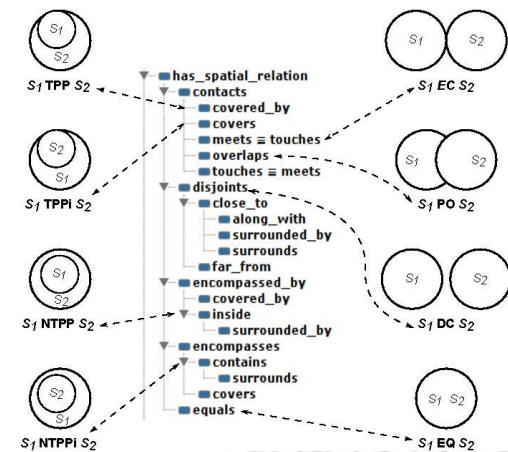
Semantic Modelling

Development of the domain knowledge of Boden in the form of an ontology (OntoCity)

>100 000 objects stored in the ontology from the map

Spatial Relations (along_with, close_to, ...) RCC8

Contains information about objects and their functions, affordances



Exploiting the **semantics**

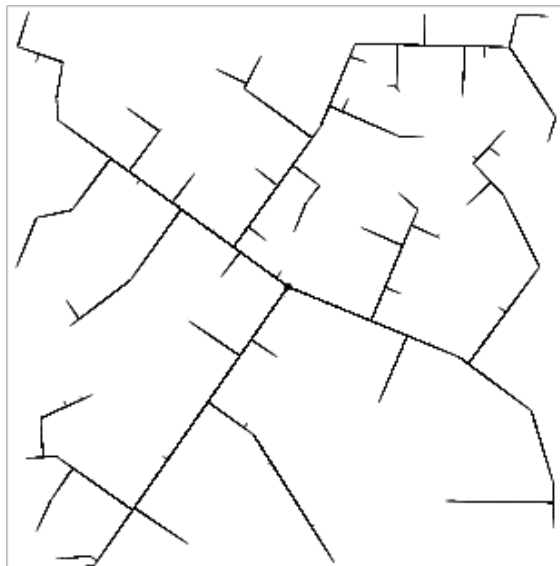
Aerial Path Planner Scenario:

▫ Scenario: simulating a drone flying over the city within a certain elevation range

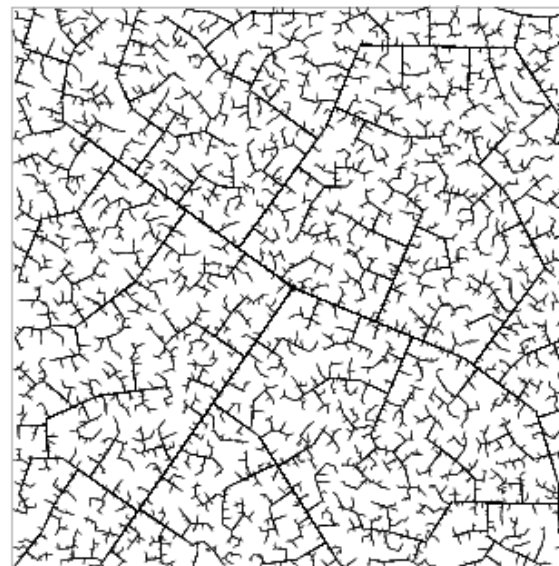
▫ **RRT Path Planner** (*LaValle, Steven M. October 1998*)

-RRT (Rapidly-Exploring Random Tree)

-Is good at quickly finding a workable path



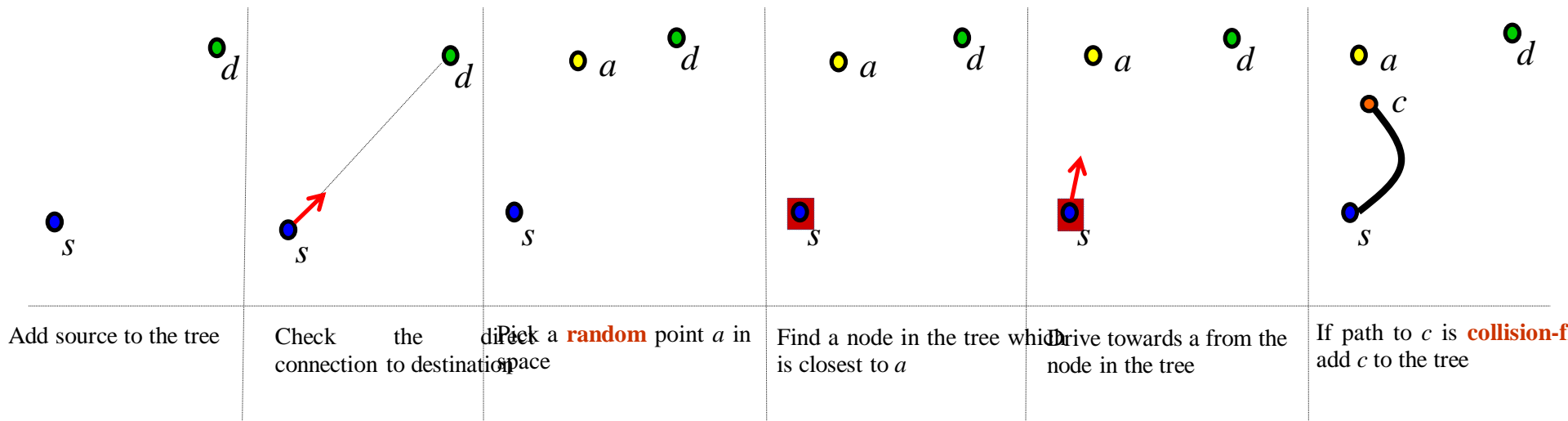
45 iterations



2345 iterations

Scenario: simulating a drone flying over the city within a certain elevation range

RRT Path Planner (LaValle, Steven M. October 1998)

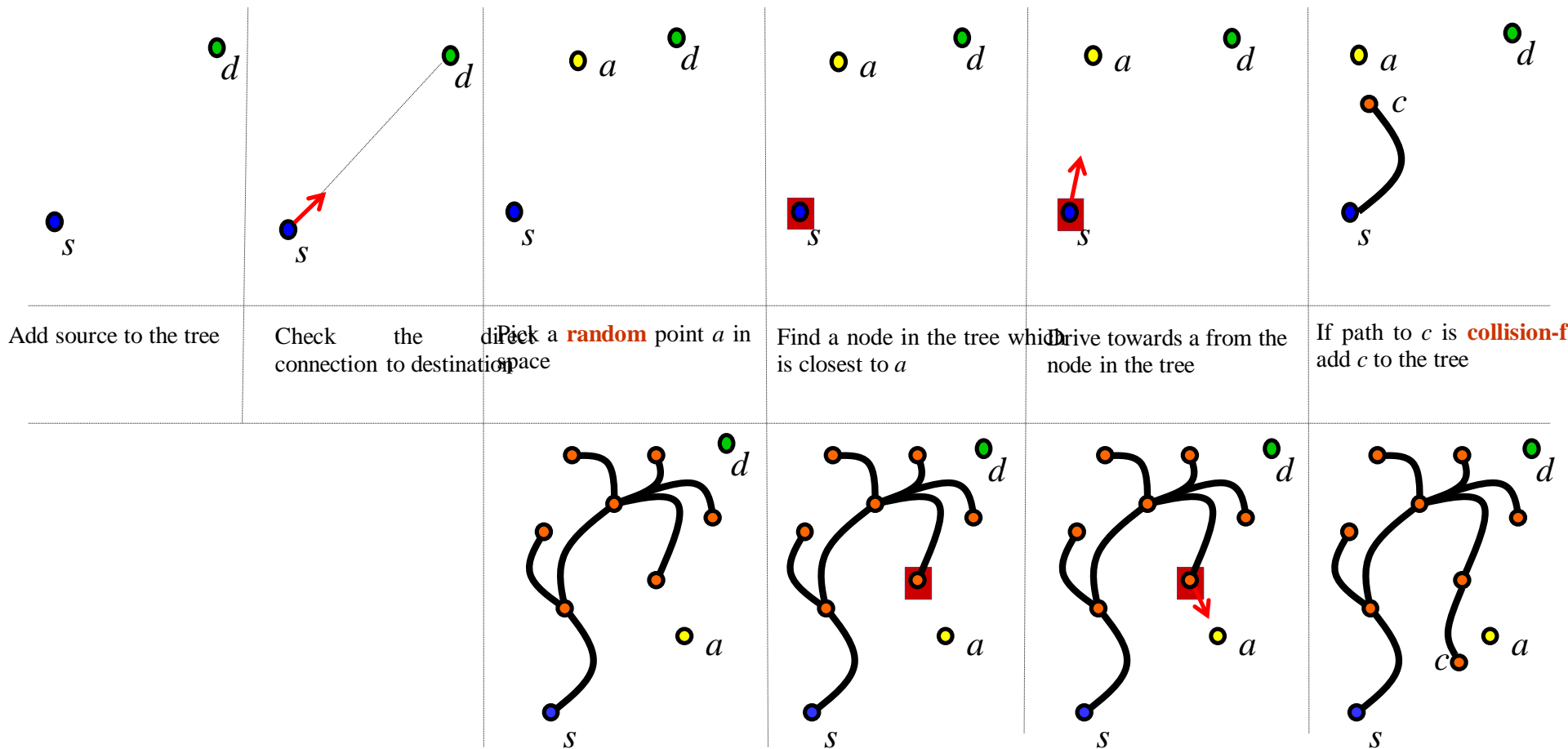


(II) Exploiting the semantics ... Aerial Path Planner Scenario: x



Scenario: simulating a drone flying over the city within a certain elevation range

RRT Path Planner (LaValle, Steven M. October 1998)



→ **Collision Checking**

✓Based on the **Elevation** values of the regions (avoiding the obstacles)

✓Based on the **Semantics** of the regions (→ a preliminary version implemented)



No-constraint (only elevation)



Avoiding hospitals

→ **Collision Checking**

✓ Since RRT is not complete, it may not find a path when there is semantic constraints



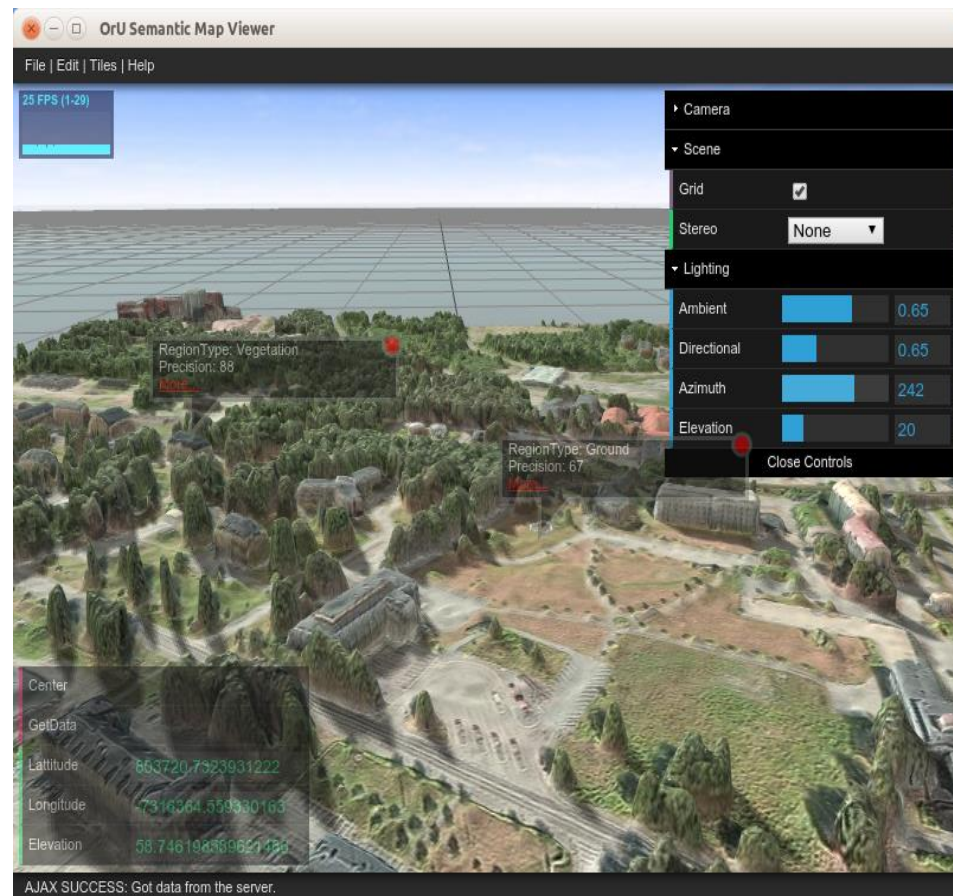
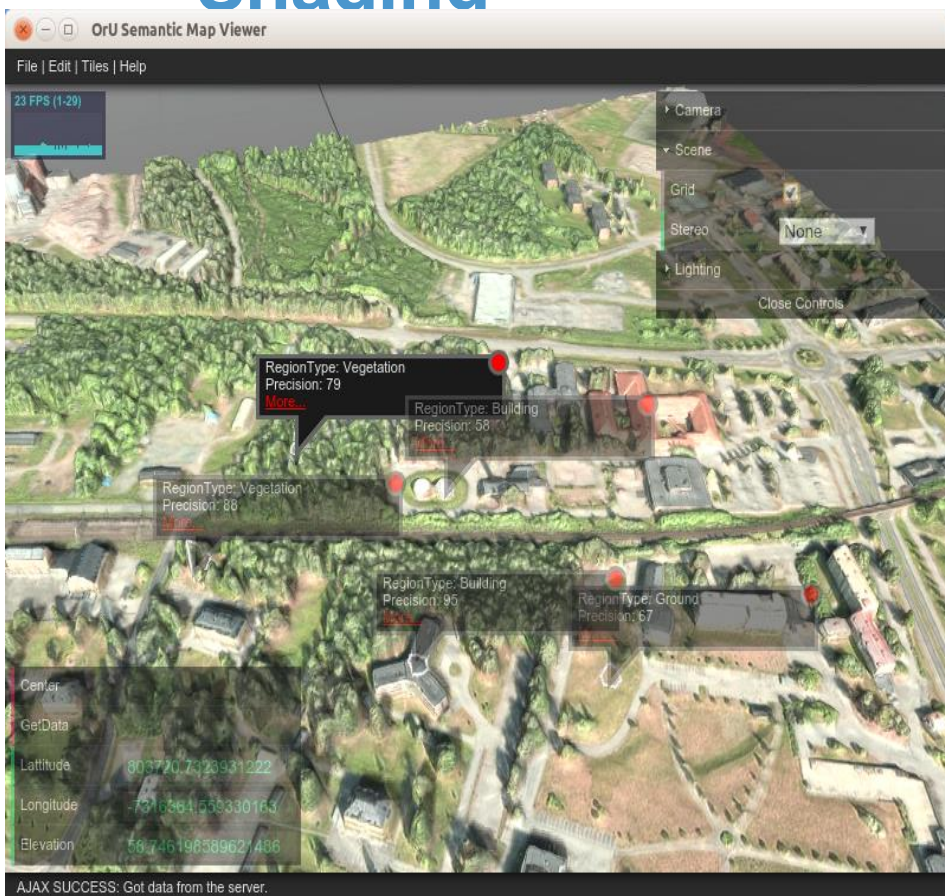
No-constraint (only elevation)



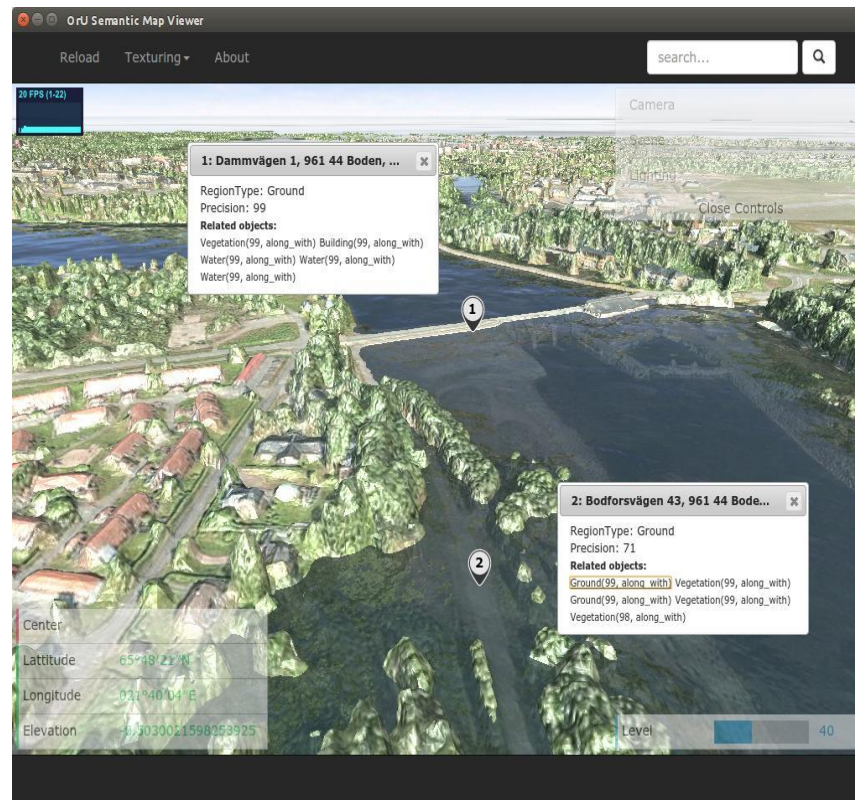
Avoiding Water

✓ The **sampling process** needs to be guided by the **semantics**

SemMap Client 2.0: Labels and Shading

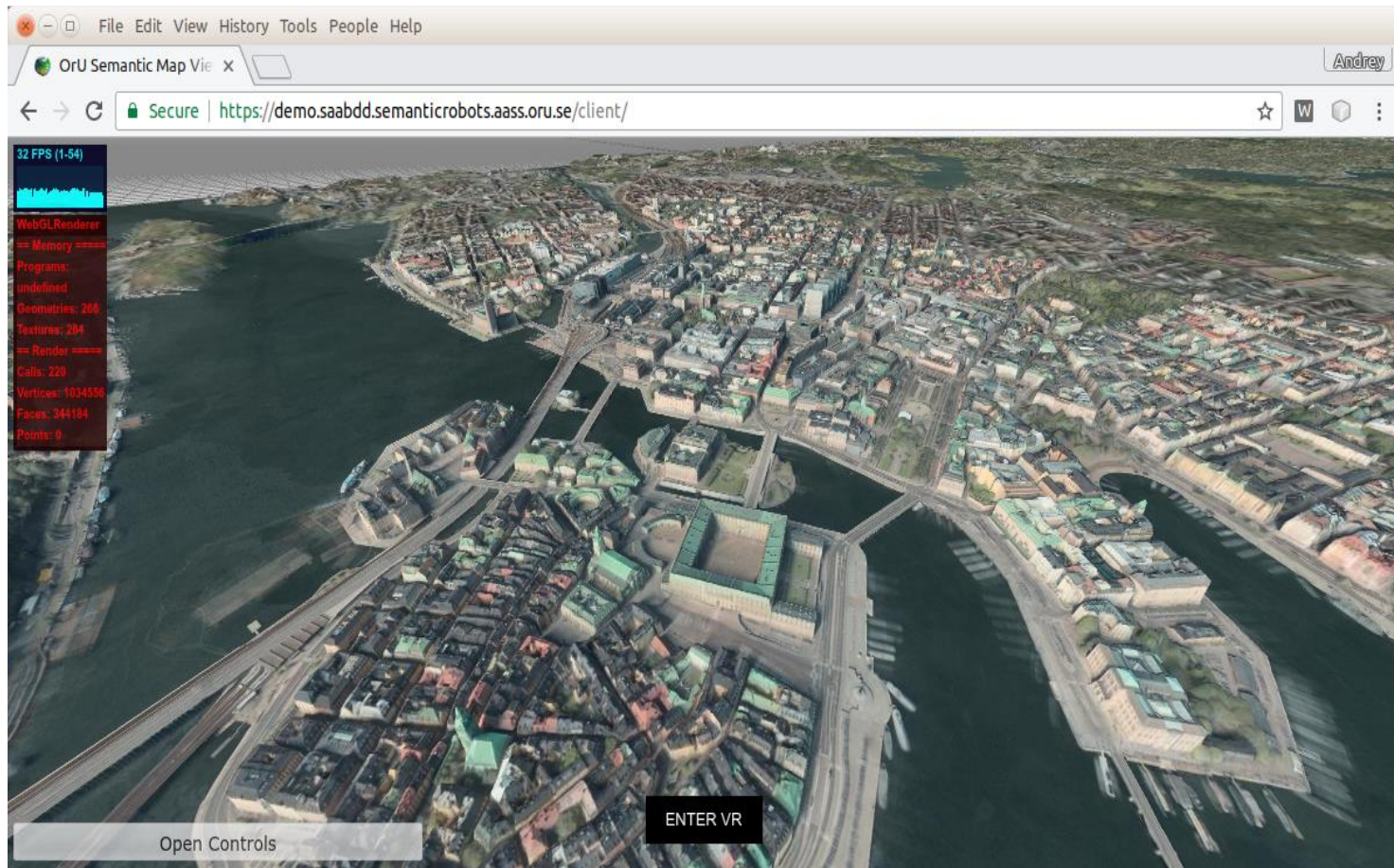


SemMap Client 2.1: Disaster Simulation

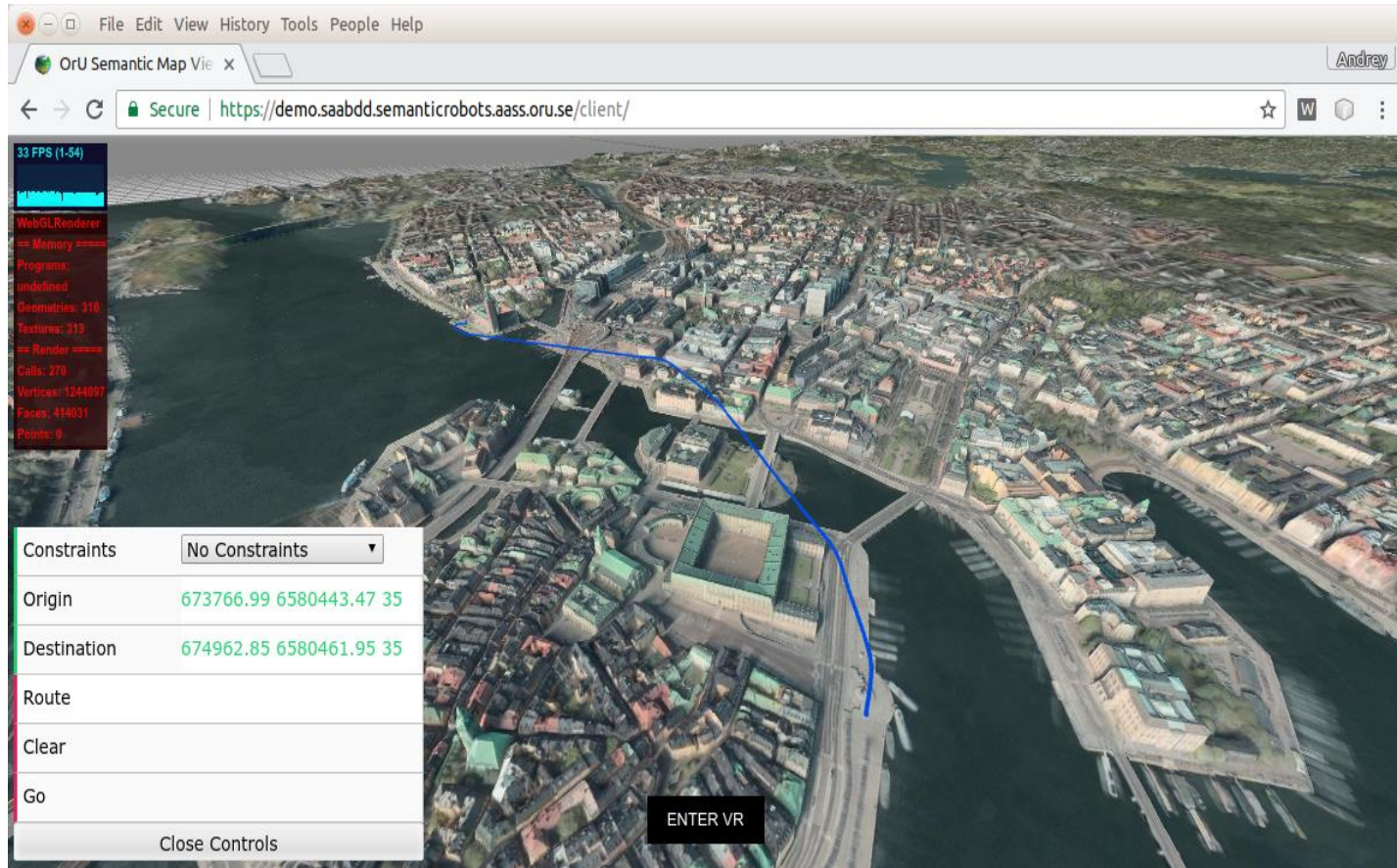


Flood simulation with the labels showing the Poi data when it is not flooded

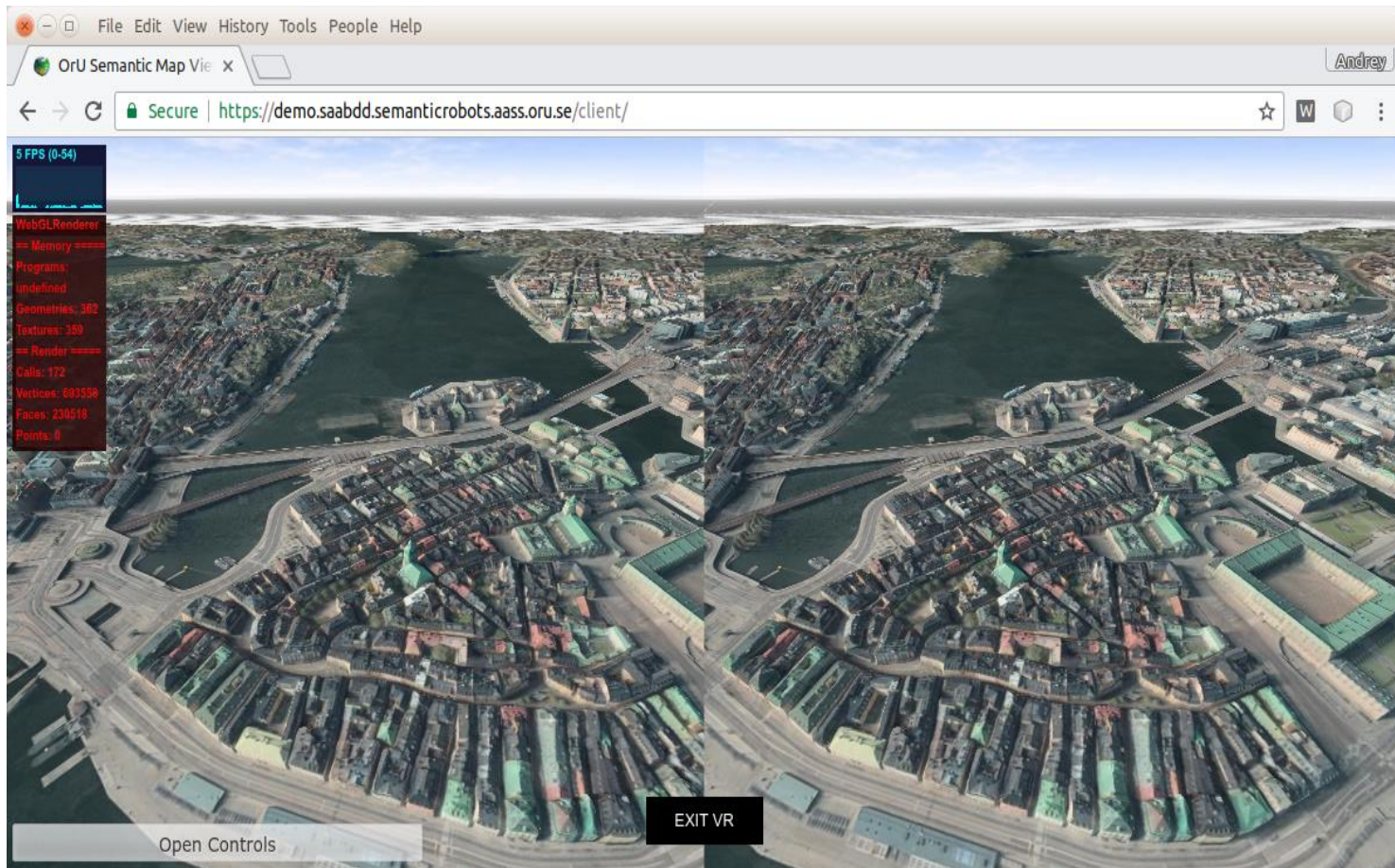
SemMap Client 3.0: Stockholm!



SemMap Client 3.0: Path Visualization

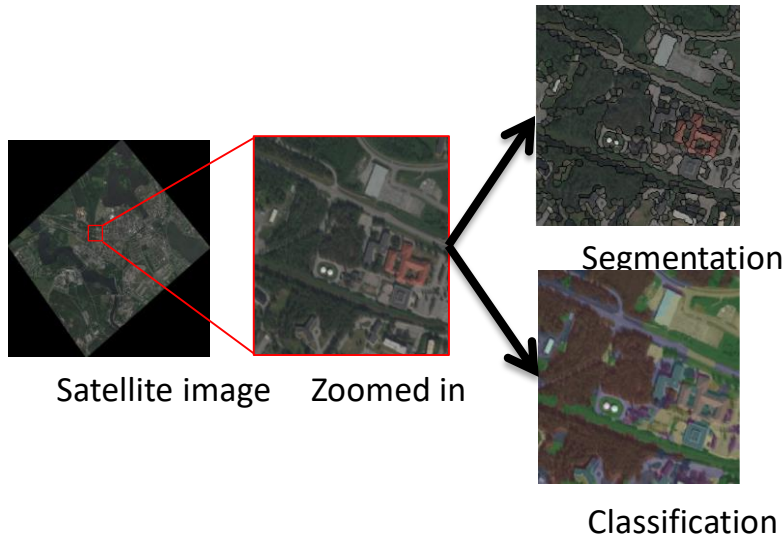


SemMap Client 3.0: VR



Full Pipeline from data to knowledge

WP1

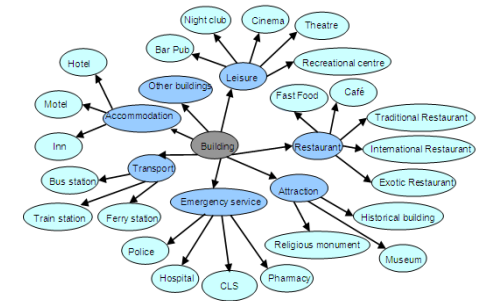


WP2



Object extraction
and maintenance
e.g. building 32,
Address, functions,
long/lat.

WP3



What is Semantic Perception and why is it important

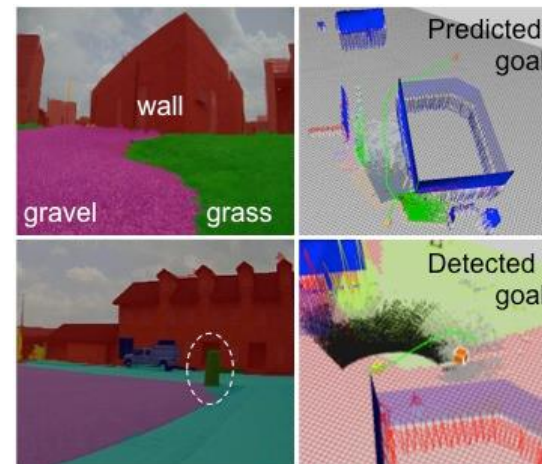
Process of augmenting sensor data into abstract, and typically, symbolic representations

It is important as it facilitates:

- Processes such as planning for robotics (e.g. Lift the crate)

- Integration of automated reasoning with sensor data

Semantic Perception requires meaningful semantics i.e. Shared and with relations between the concepts.





Thank you