# Efficient Object-Level Semantic Mapping with RGB-D Cameras

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- Method
- Experiment
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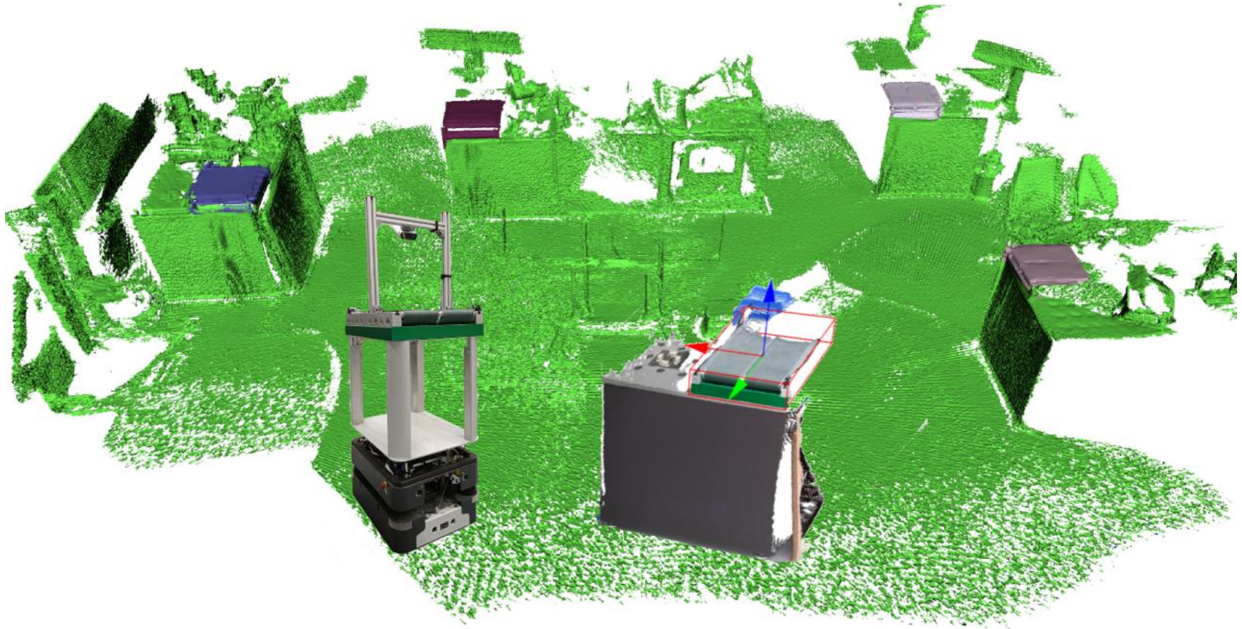
# Background and Tasks

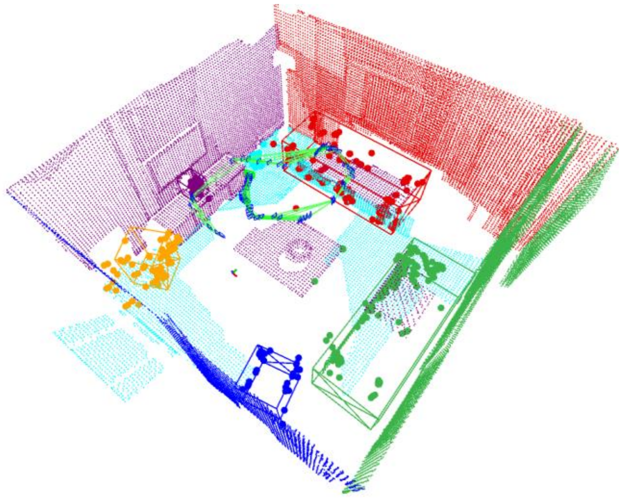
- Scene understanding in unknown environment (3D object segmentation)
- Efficient semantic mapping (voxblox++)
- Field expriment on Agiprobot project



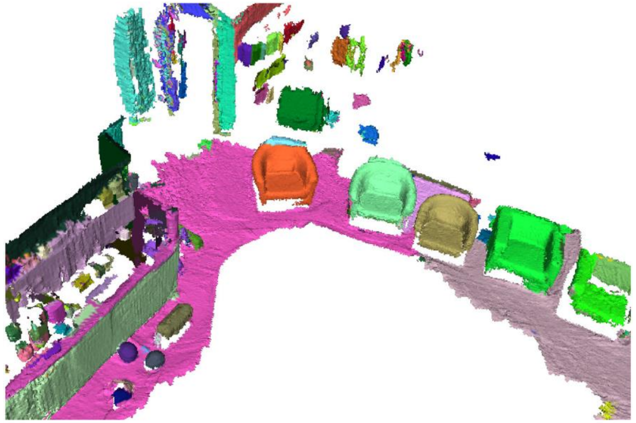
# Literature Review

- Semantic mapping
- Object-level semantic mapping

| Method | Year | Sensors | Object model | Semantic/ object-oriented | Map Type | usage |
|---|---|---|---|---|---|---|
| Zhou et al Structure SLAM | 2022 | RGB-D | Geometric cuboid | Object-oriented | Feature point map | Localization |
| Sünderhauf et al. Meaningful map | 2014 | RGB-D | Point cloud model | Object-oriented | Point cloud map | Scene understanding |
| Nakajima et al, Efficient | 2018 | RGB-D | Point cloud model | Semantic | Point cloud map | Scene understanding |
| McCormac et al. Semantic Fusion | 2016 | RGB-D | Surfel-based model | semantic | Point cloud map | Scene understanding |
| Pham et al | 2016 | RGB-D | Voxel model | Object-oriented | Voxel map | Interactive application, object manupulation and picking |
| Grinvald et al Voxblox ++ | 2019 | RGB-D | Voxel model | Object-oriented | Voxel map | Scene understanding, navigation |
| Li et al Incremental | 2020 | RGB-D | Voxel model | Object-oriented | Voxel map | Navigation and manipulation |
| Mascaro et al Voxblox fusion | 2022 | RGB-D LiDAR | Voxel model | Object-oriented | Voxel map | Interactive application |

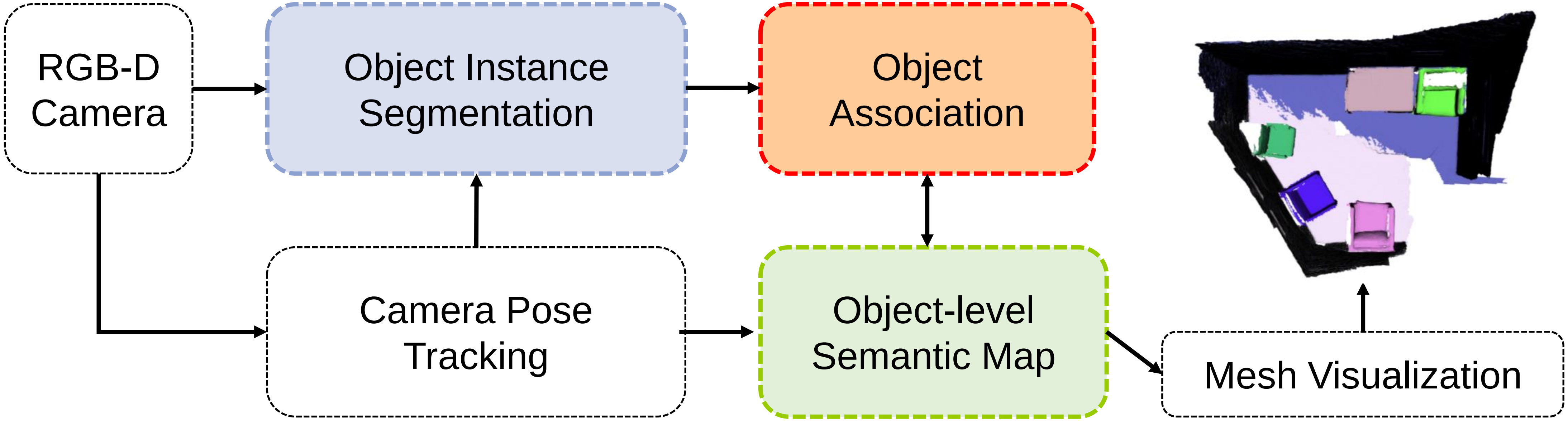


Feature Point Map
Structure SLAM 2019



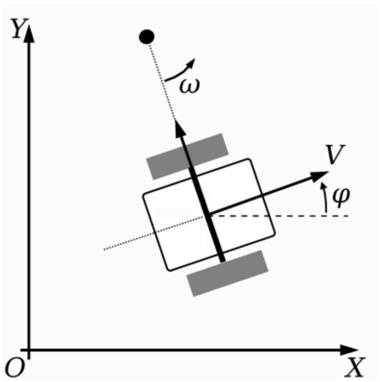
Voxel object-oriented map
Voxblox++, 2019

# Method: Framework

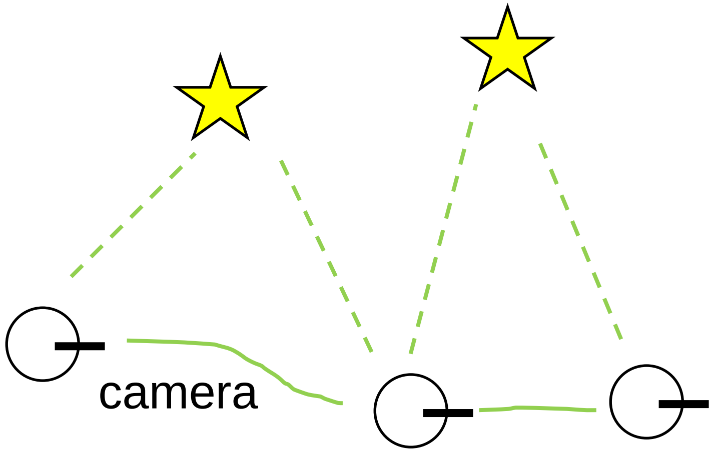


# Method: Camera Poses Tracking

- Camera poses tracking methods:
  - Wheel encoder
  - Feature tracking
  - Laser scan matching

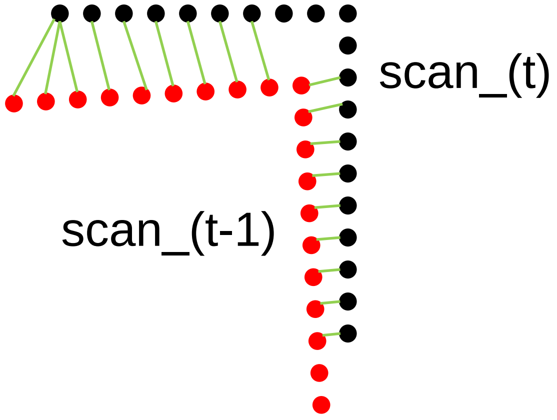



$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} x \\ y \\ z \end{pmatrix} + \begin{pmatrix} \cos\varphi & 0 \\ \sin\varphi & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} v \\ w \end{pmatrix}$$




$$C^*, L^* = \underset{c,l}{argmin} \sum \|e\|^2$$

camera | landmark | constraints

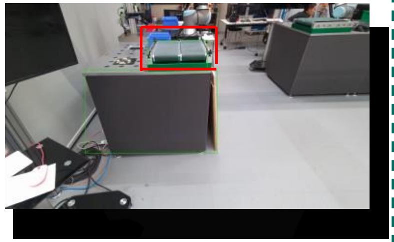



$$C^* = \underset{i,j}{argmin} \sum \left\|P_i - P_j\right\|^2$$

camera | matched points

# Method: Object Segmentation

**RGB-D** Input



Point cloud extraction →

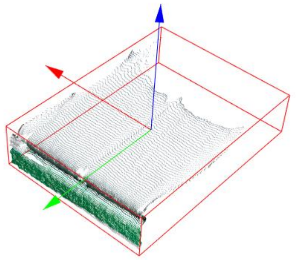
**Bbox Points**

Outlier exclusion →

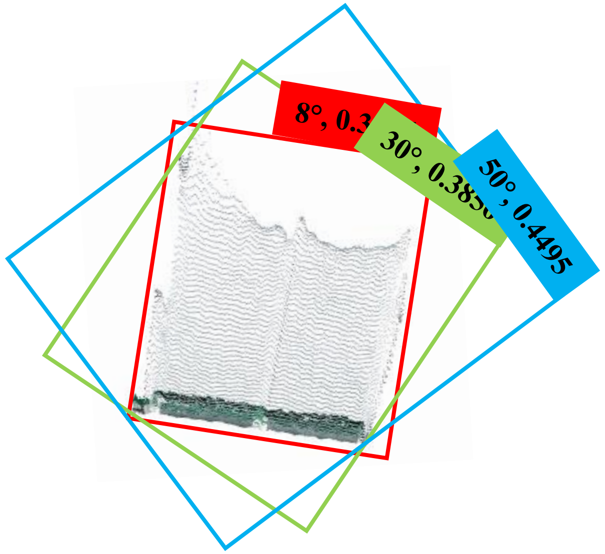
**Object Points**

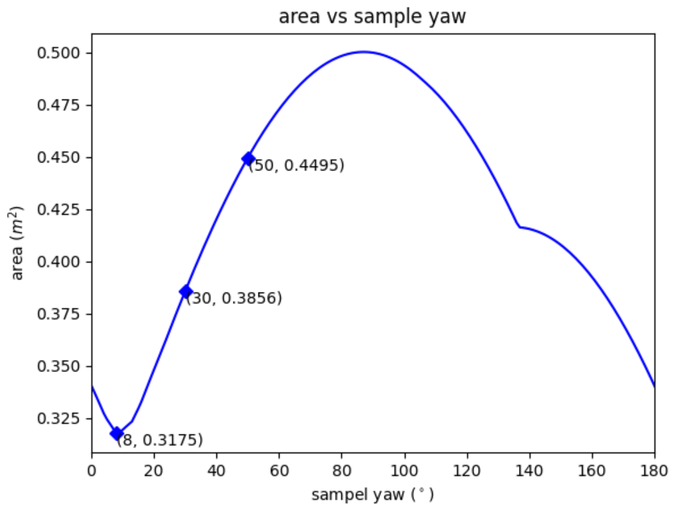
Cuboid Generation →

**Geometry**

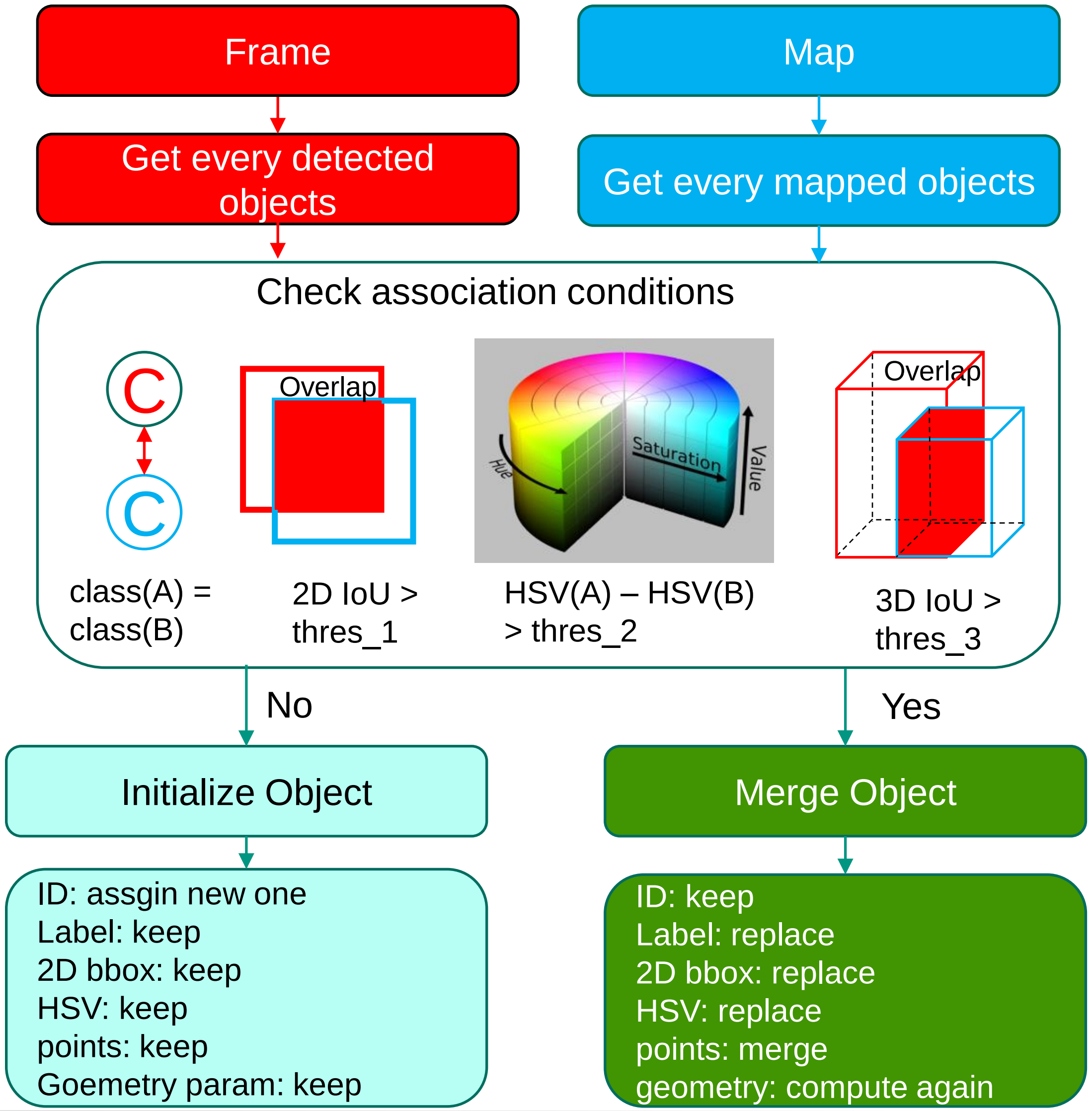


Why do we detect conveyor?
>> small, can be fully observed
>> cuboid shape, accurate detection
>> can act as navigation goal



# Method: Object Association

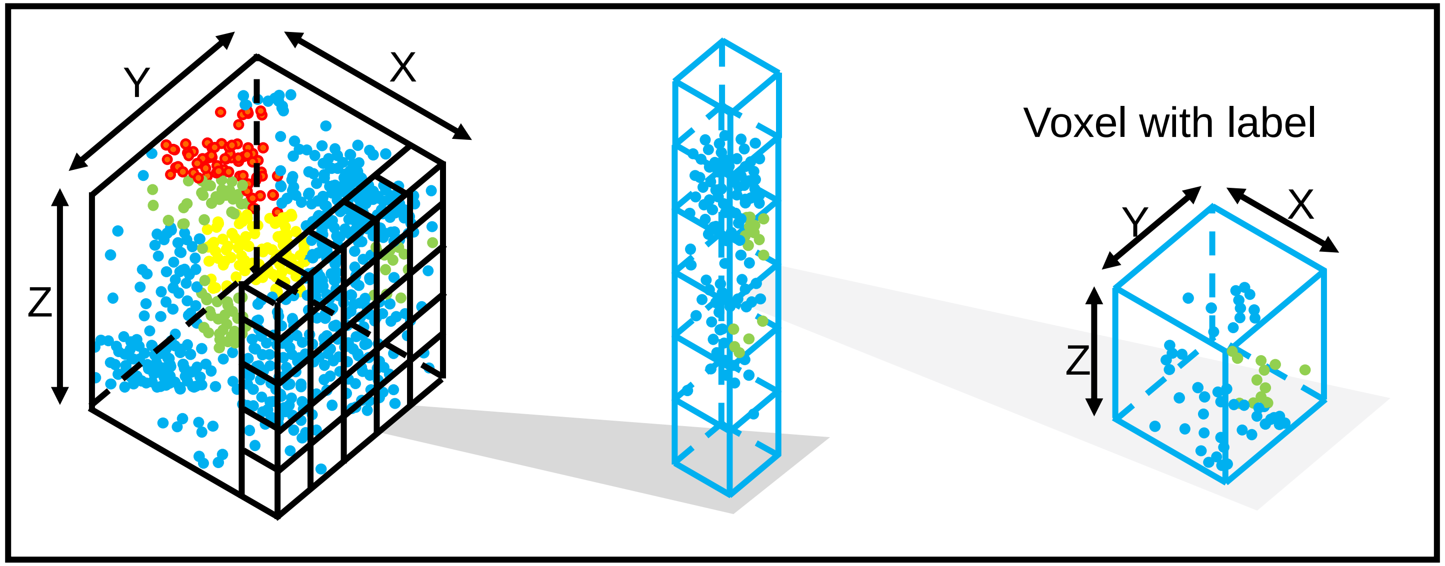



- Association
  - Label
  - 3D bbox IoU (maybe label is not correct)
  - 2D bbox IoU
  - HSV
  - >> Init frame objects to map objects or update existing objects

- How to update object information:
  - ID -> update related to associated result
  - label-> same
  - points-> merge, probabilistic
  - HSV -> replace
  - 9 DoF -> update, calculate again.

# Methods: Object-level Semantic Map

- Why voxel-based map
  - 3D occupancy information: interactive application, such as navigation and picking
  - Efficient: CPU real-time solution (from voxblox)




- Convert object points to voxel-based model
  - Voxel size: 2cm
  - Voxel param: label info, occupancy info, position info

- Voxel label update strategy
  - Voxel labels collection

$$\varphi(v, l_i) \leftarrow \varphi(v, l_i) + 1$$

  - Update voxel label by counting the maximum class

$$\big(L(v)\big) = \underset{i}{\operatorname{argmax}}\, \varphi(v, l_i)$$

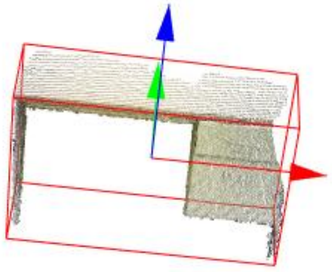
# Experiments

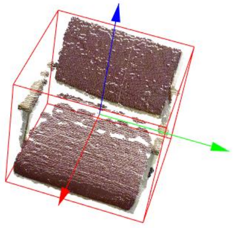
- Indoor dataset: SceneNN dataset
- Logistic dataset: Agiprobot

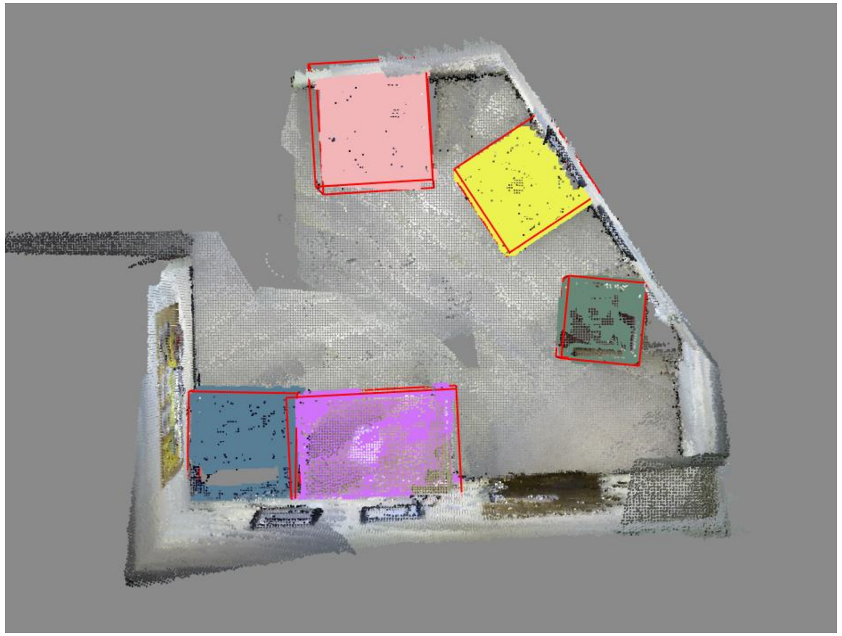
Source: https://github.com/hkust-vgd/scenenn

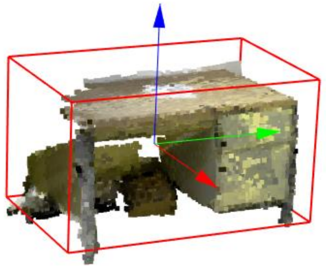
# Experiments

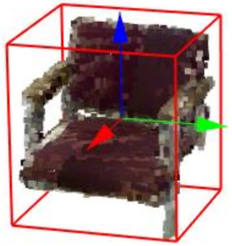
- Example

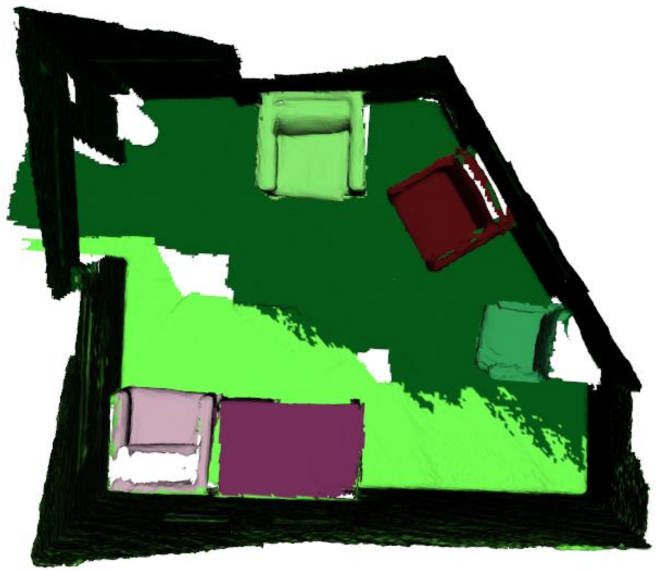










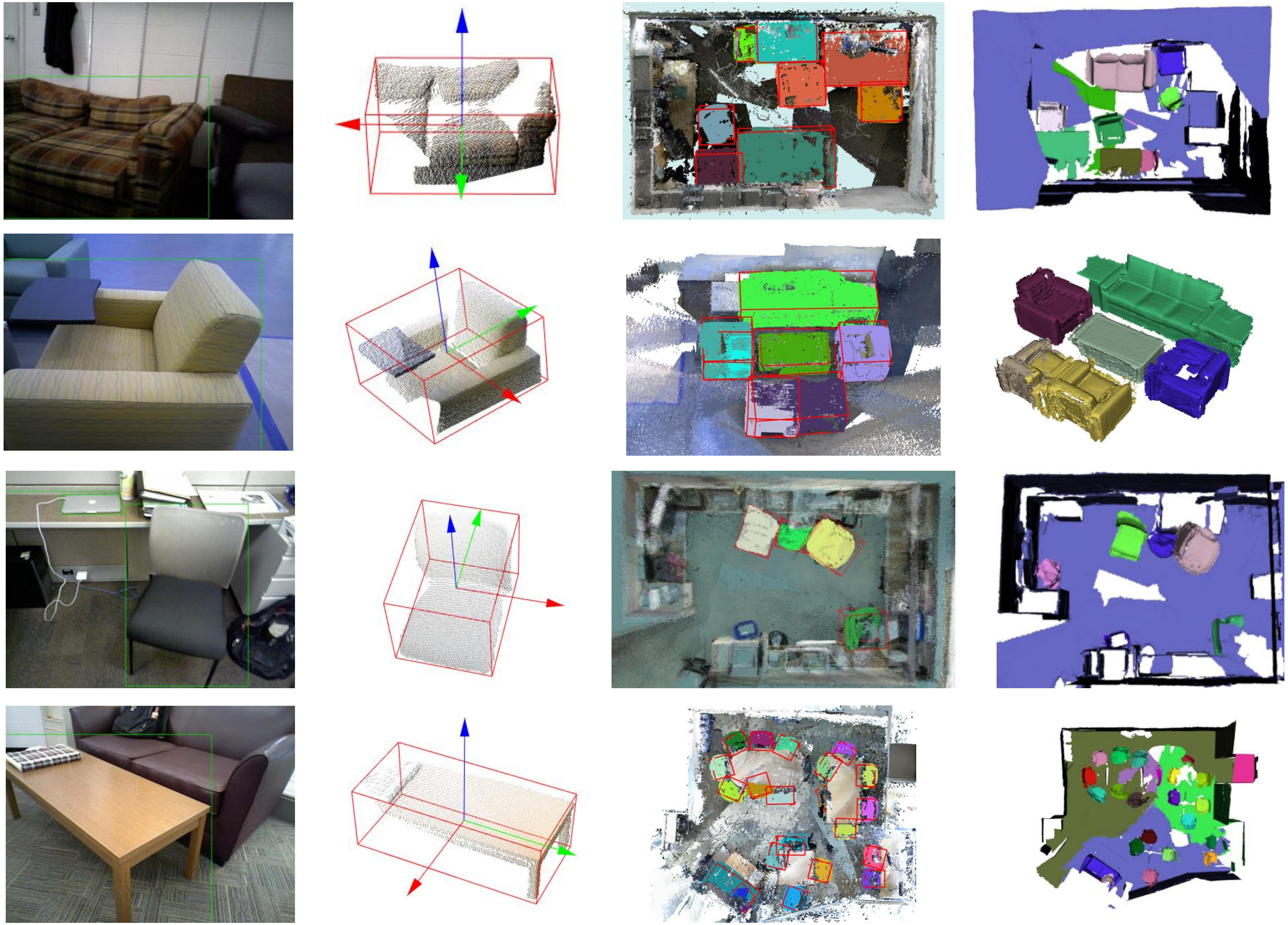


030

061

086

206



# Experiment: SceneNN dataset

## Average 3D IoU

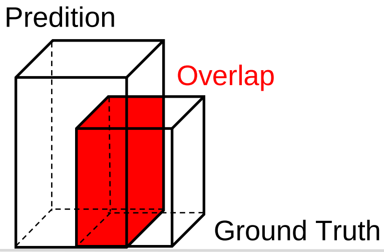
| Sequence ID | Bed | Chair | Sofa | Table | Books | refrigerator | Television | Toilet | Bag | Avg.(Ours) |
|---|---|---|---|---|---|---|---|---|---|---|
| 011 | - | 70.2 | 70.2 | **86.3** | - | - | - | - | - | 78.3 |
| 016 | 51.3 | - | 71.9 | 0 | | | | | | 41.1 |
| 030 | - | 57.6 | **80.4** | **85.7** | 0 | - | - | - | - | 57.4 |
| 061 | - | 74.5 | 62.7 | **95.1** | | | | | | 77.4 |
| 078 | - | 45.9 | - | 0 | 0 | 67.8 | - | - | - | 13.9 |
| 086 | - | 58.2 | - | 0 | 0 | - | - | - | 53.8 | 56 |
| 096 | 63.1 | 60.9 | - | 0 | - | - | 32.3 | - | 0 | 31.3 |
| 206 | - | 56.5 | 23.3 | 65.5 | - | - | - | - | 29.6 | 43.7 |
| 223 | - | 63.7 | - | 69.2 | - | - | - | - | - | 66.5 |
| 255 | - | - | - | - | - | 55.8 | - | - | - | 55.8 |

## mAP@0.5

| Sequence ID | Bed | Chair | Sofa | Table | Books | refrigerator | Television | Toilet | Bag | Avg.(Ours) |
|---|---|---|---|---|---|---|---|---|---|---|
| 011 | - | **100** | **100** | **100** | - | - | - | - | - | 100 |
| 016 | **100** | - | **100** | 0 | | | | | | 66.7 |
| 030 | - | 72 | **100** | 66.7 | 0 | - | - | - | - | 59.7 |
| 061 | - | 62.5 | **100** | 33.3 | - | - | - | - | - | 65.3 |
| 078 | - | 50 | - | 0 | 0 | **100** | - | - | - | 37.5 |
| 086 | - | 75 | - | 0 | 0 | - | - | - | 50 | 31.3 |
| 096 | **100** | **100** | - | 0 | 0 | - | 0 | - | 0 | 33.3 |
| 206 | - | 41 | 0 | 40 | - | - | - | - | 0 | 20.3 |
| 223 | - | **100** | - | 50 | - | - | - | - | - | 75 |
| 255 | - | - | - | - | - | **100** | - | - | - | 100 |

3D Intersection over Union (IoU)

$$IoU_{3D} = \frac{V_{overlap}}{V_{gt} + V_{pred} - V_{overlap}}$$




mAP: mean average precision
TP: True Positive: IoU>=0.5
FP: False Positive : IoU<0.5

$$mAP = \frac{1}{|classes|} \sum_{c \in classes} \frac{|TP_c|}{|TP_c| + |FP_c|}$$

# Experiment: SceneNN dataset

## runtime performance

| Module | Time-CPU (ms) | Time-GPU (ms) |
|---|---|---|
| Object Detection | 725 | 32 |
| Object Segmentation | 17.85 | 15 |
| Object Mapping | 299 | 50 |
| Total | 1024 | 102 |

## mAP comparison

| **Method** | 011 | 016 | 030 | 061 | 078 | 086 | 096 | 206 | 223 | 225 | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Pham et al [1] | 52.1 | 34.2 | 56.8 | 59.1 | 34.9 | 35.0 | 26.5 | 41.7 | 40.9 | 48.6 | 43.0 |
| Grinvald et al [2] | 75.0 | 33.3 | 56.1 | **66.7** | 45.2 | 20.0 | 29.2 | **79.6** | 43.6 | 75.0 | 54.4 |
| Li et al [3] | 78.6 | 25.0 | 58.6 | 46.6 | **69.8** | **47.2** | 26.7 | 78.0 | 45.8 | 75.0 | 55.1 |
| ours | **100** | **66.7** | **59.7** | 65.3 | 37.5 | 31.3 | **33.3** | 20.3 | **75** | **100** | **58.9** |

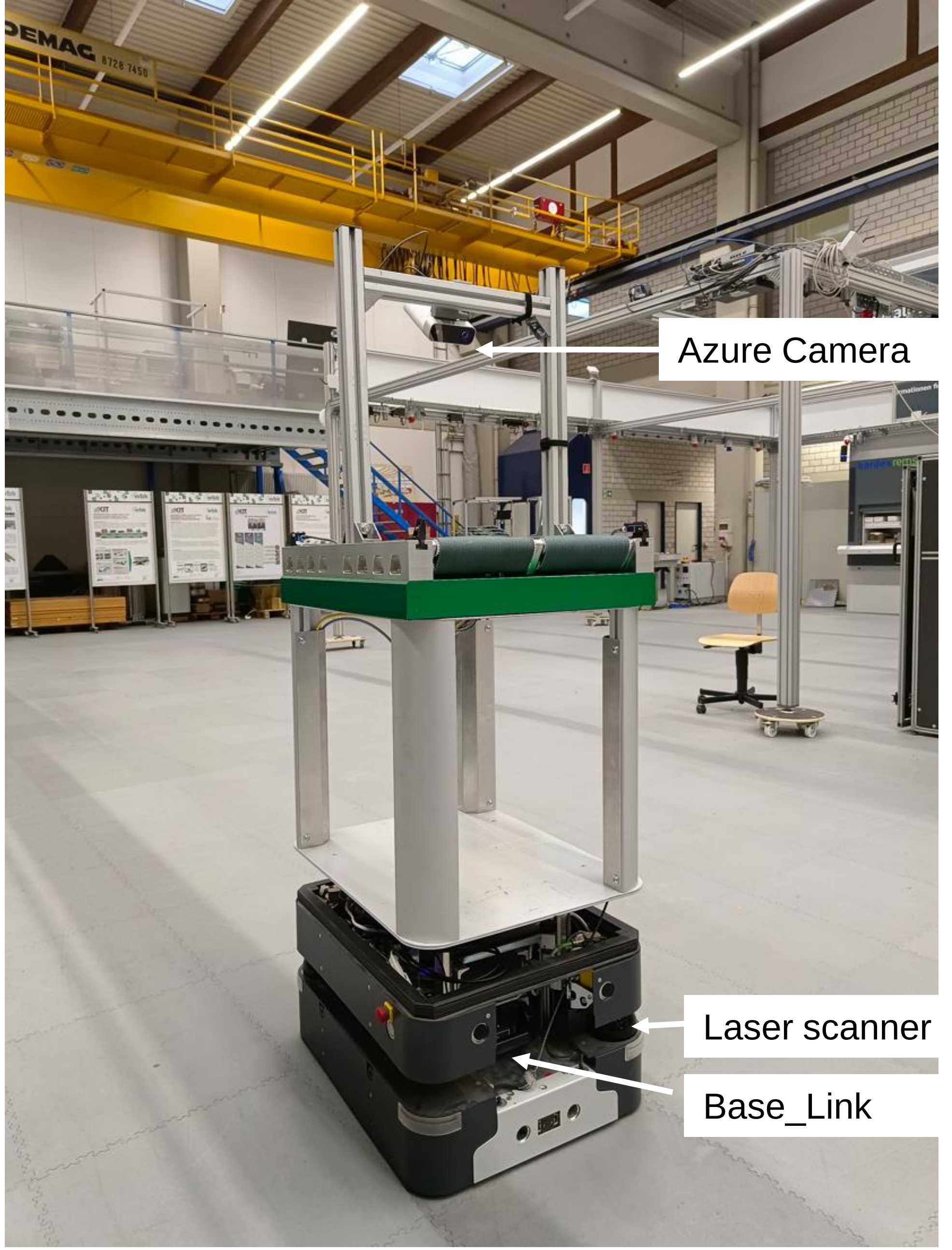
## runtime comparison

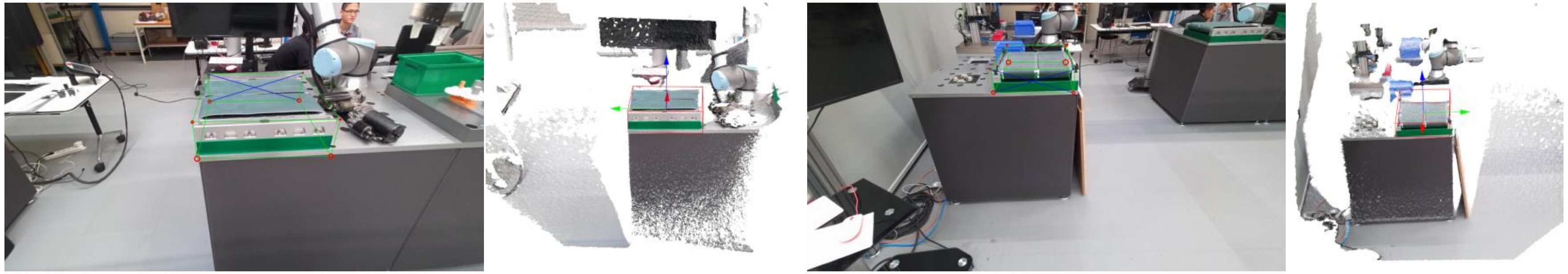
| **Method** | **Representation** | **FPS** |
|---|---|---|
| Pham et al [1] | Instance-oriented | 1 Hz |
| Grinvald et al [2] | Instance-oriented | 1 Hz |
| Li et al [3] | Instance-oriented | 10.8 Hz |
| Ours-CPU | Instance-oriented | 1 Hz |
| Ours-GPU | Instance-oriented | 20 Hz |

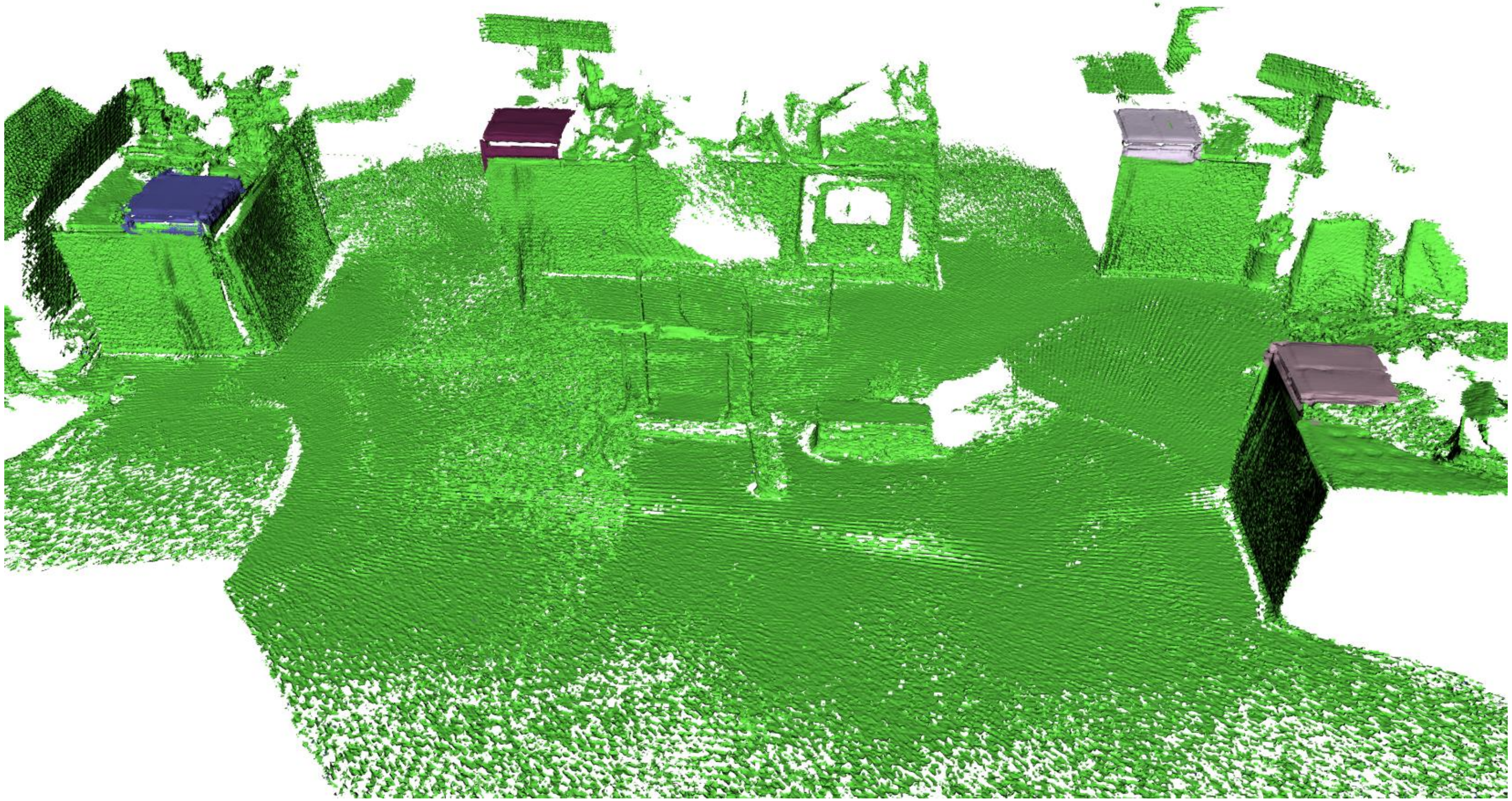
# Experiment: Agiprobot

- Setting:
- Controller: CPU
- Camera: Microsoft Azure Kinect
- Laser scanner: SICK
- Camera laser calibration:

- Scene size: 6x12m
- Detect objects: conveyor







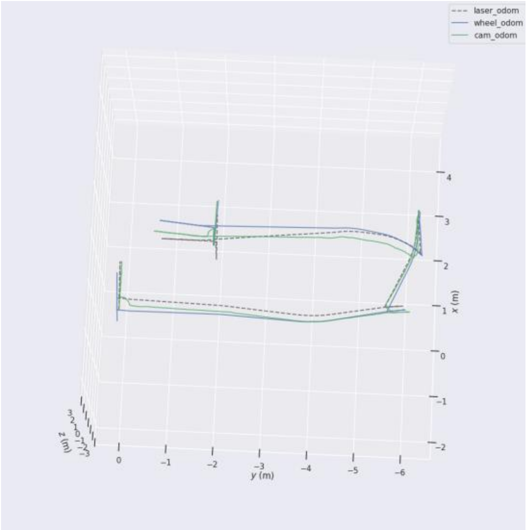
# Experiment: Agiprobot

Table: Object IoU

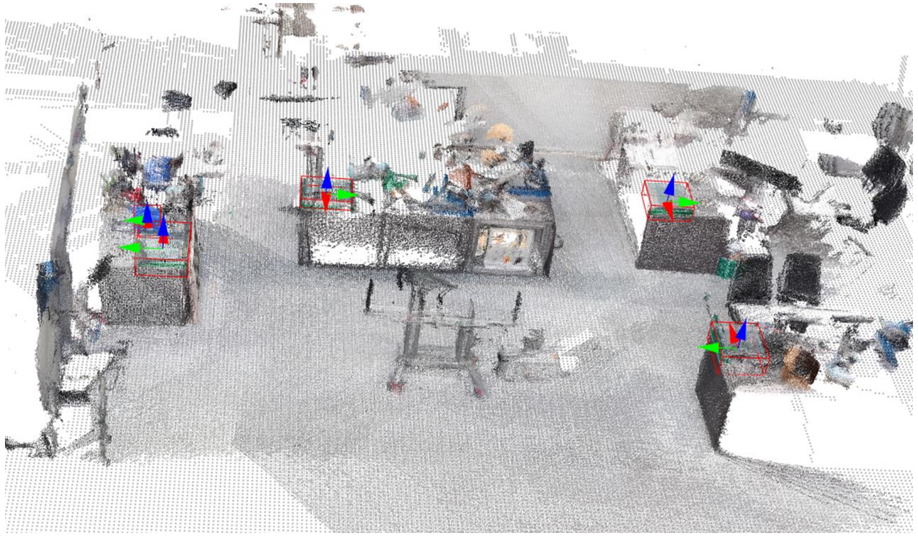
| Conveyor | 3D IoU | E_Trans(m) | E_rot (°) |
|---|---|---|---|
| 1 | 0.7446 | 0.058 | 3.4 |
| 2 | 0.7140 | 0.060 | 0.9 |
| 3 | 0.´8061 | 0.029 | 1.6 |
| 4 | 0.9056 | 0.035 | 1.0 |
| Average | 0.7925 | 0.045 | 1.7 |

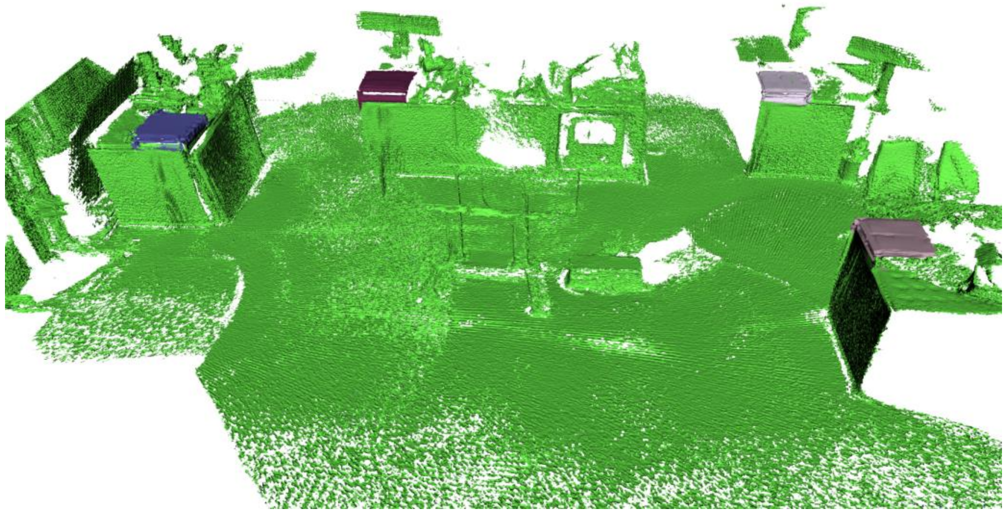
Table: runtime performance

| Module | Time-CPU(ms) |
|---|---|
| Object Detection | 725 |
| Object Segmentation | 17.85 |
| Object Mapping | 299 |
| Total | 1024 |



Camera poses tracking


Point cloud map


Voxel-based map

# Conclusion

- What we have done
  - Proposed an efficient object mapping method
  - Evaluate the proposed method on public dataset
  - Evaluate the proposed method on real robotic platform in logistic scene.

- Conclusion
- RQ3: How to efficiently map the environment with semantic object information? (especially in logistic environments)
- we presented an efficient object-level semantic mapping system, which takes RGB-D sequences as input to build a volumetric object-oriented map.
- Experiment on publicly indoor dataset and field test shows that our system has a comparative performance while avoiding high computational cost.
- By employing a fast and stable object detector and TSDF mapping framework, our system can be extended to a CPU-only robotic platform for real-world application.