# *DUFOMap*: Efficient Dynamic Awareness Mapping

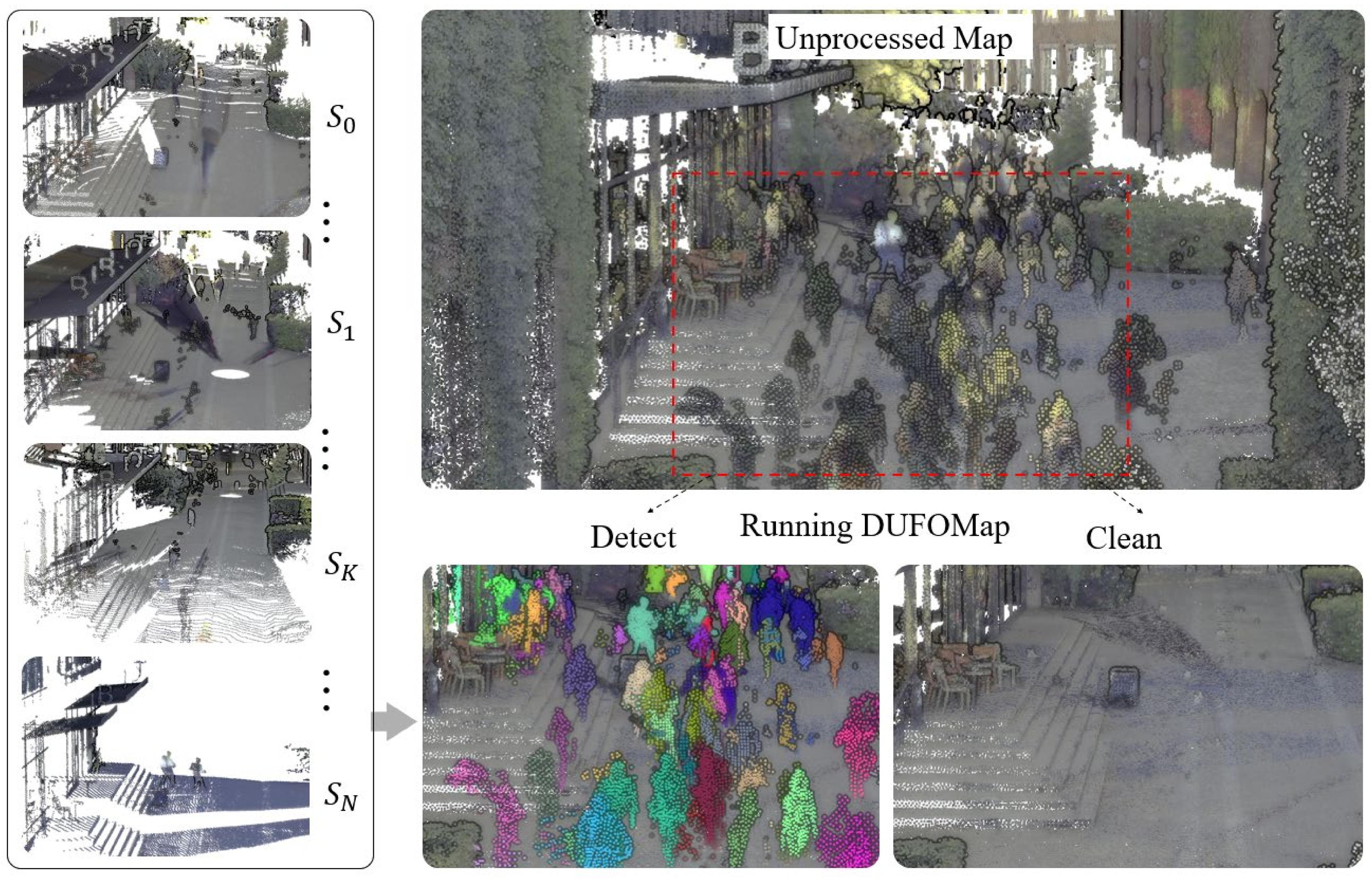
Daniel Duberg*[1], Qingwen Zhang*[1], Mingkai Jia[2], Patric Jensfelt[1]

*co-first author, [1] KTH Royal Institute of Technology, [2] Hong Kong University of Science and Technology

IROS '24 ABU DHABI

Published at *IEEE RA-L*

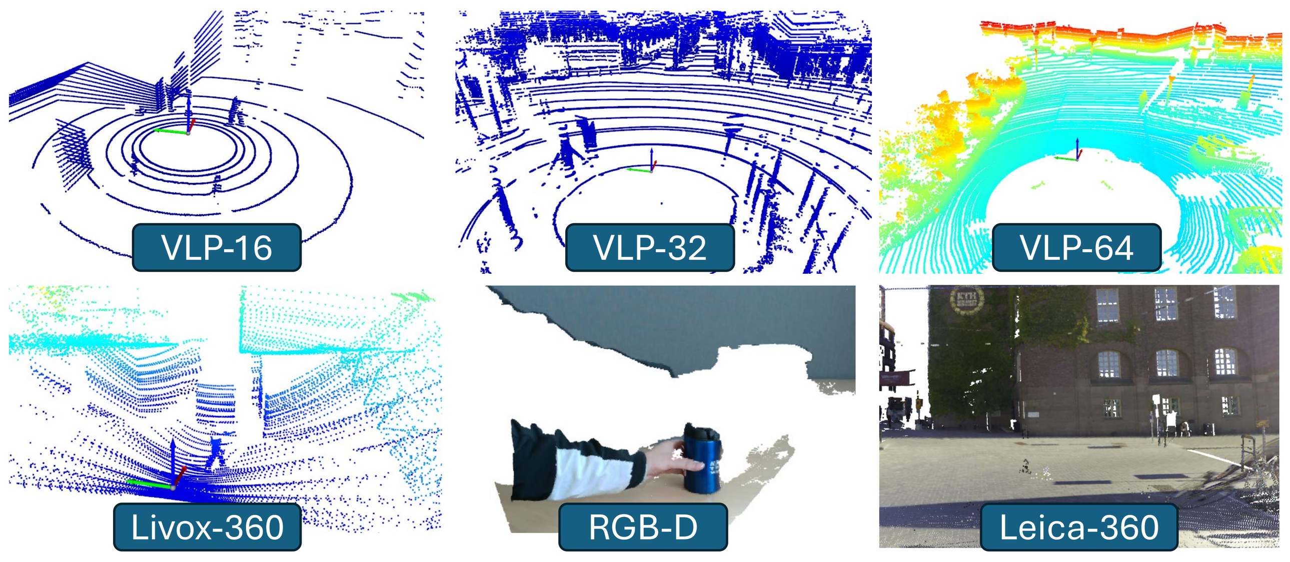
## 1. Introduction & Motivation

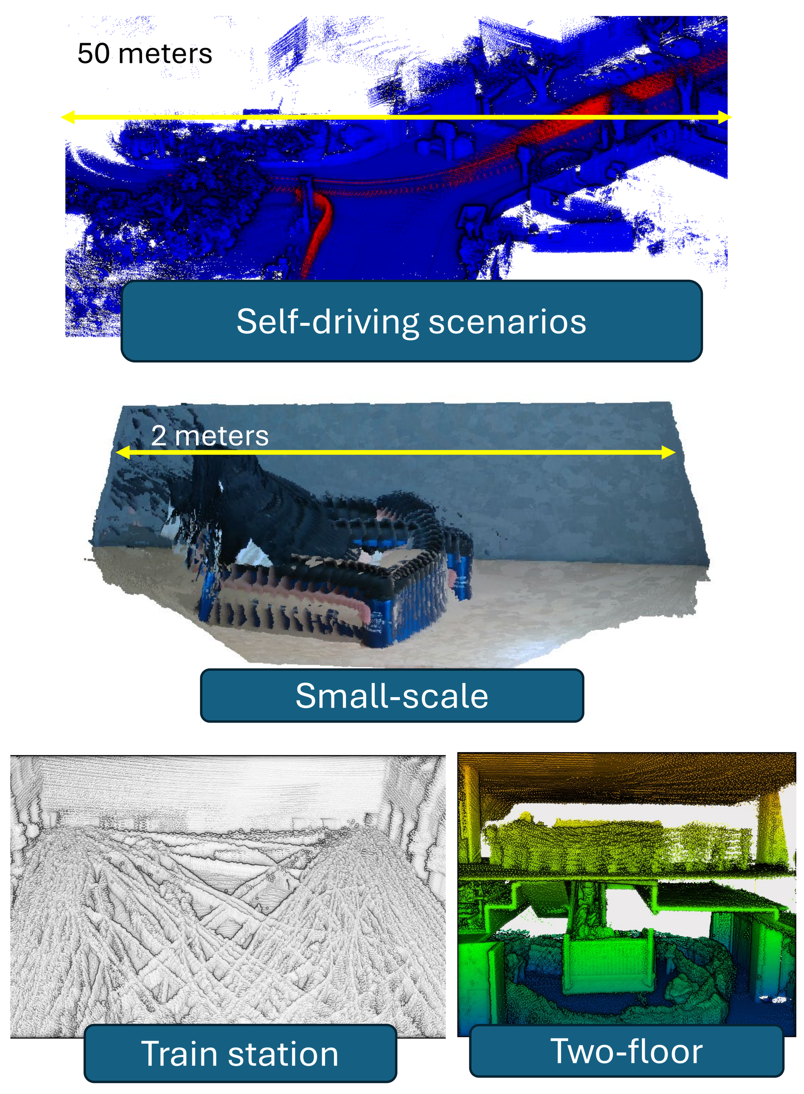



The **dynamic nature** of the real world is one of the main challenges in robotics. The first step in dealing with it is to **detect which parts of the world are dynamic**.

Many sensor types & Different scenarios & Real-time operation

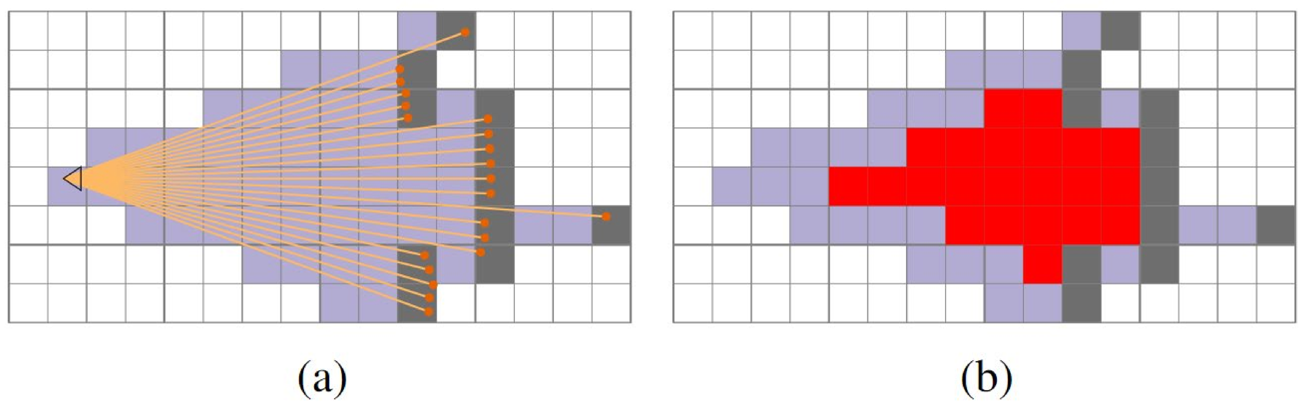
Due to these two factors, Existing methods often need **tune lots of parameter** to achieve good performance.




## 2. Method

The key insight is that if **a region has been observed as empty** at one time, **points observed** inside this region at another time have to be **dynamic**.




We propose to look not only at the direct neighbors of a voxel, but also at the **surrounding voxels** at a **Chebyshev distance** of $d_p$ away.

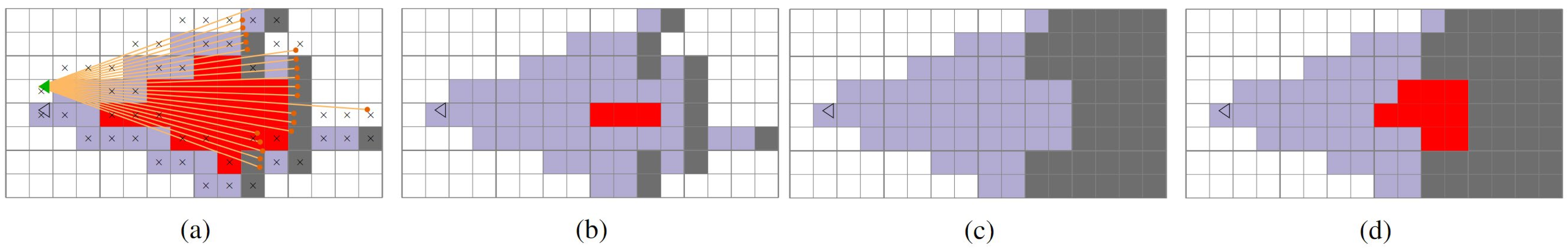
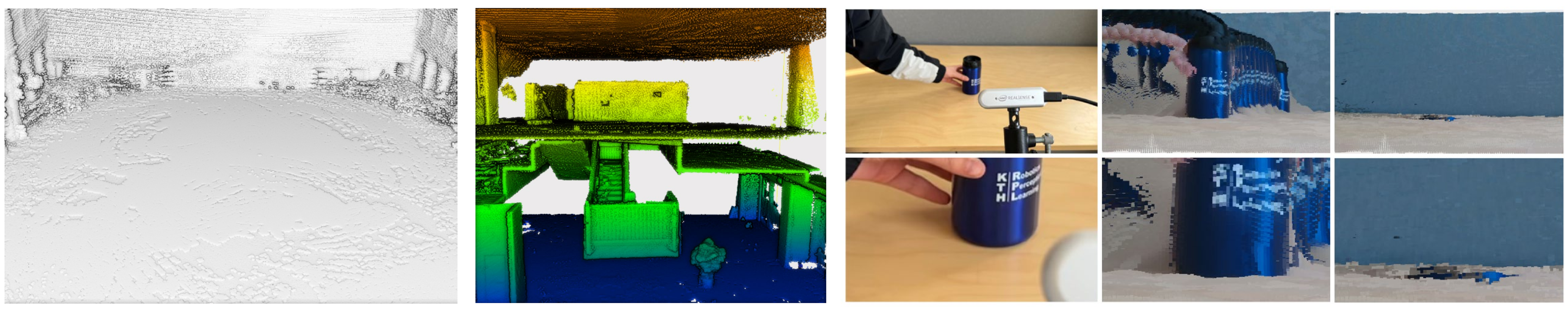
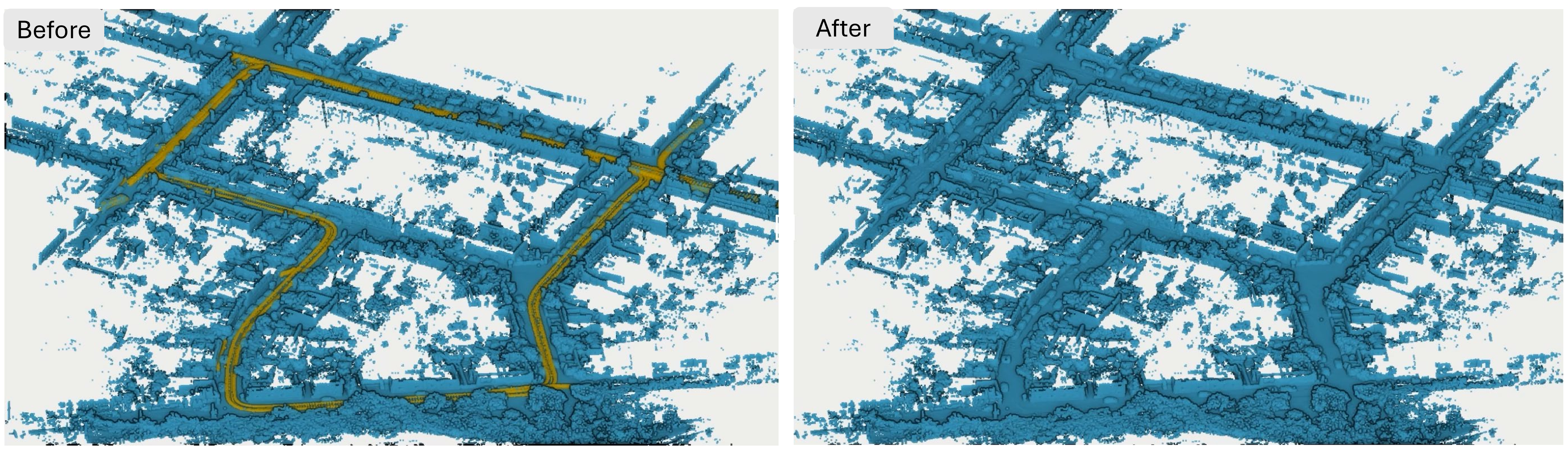
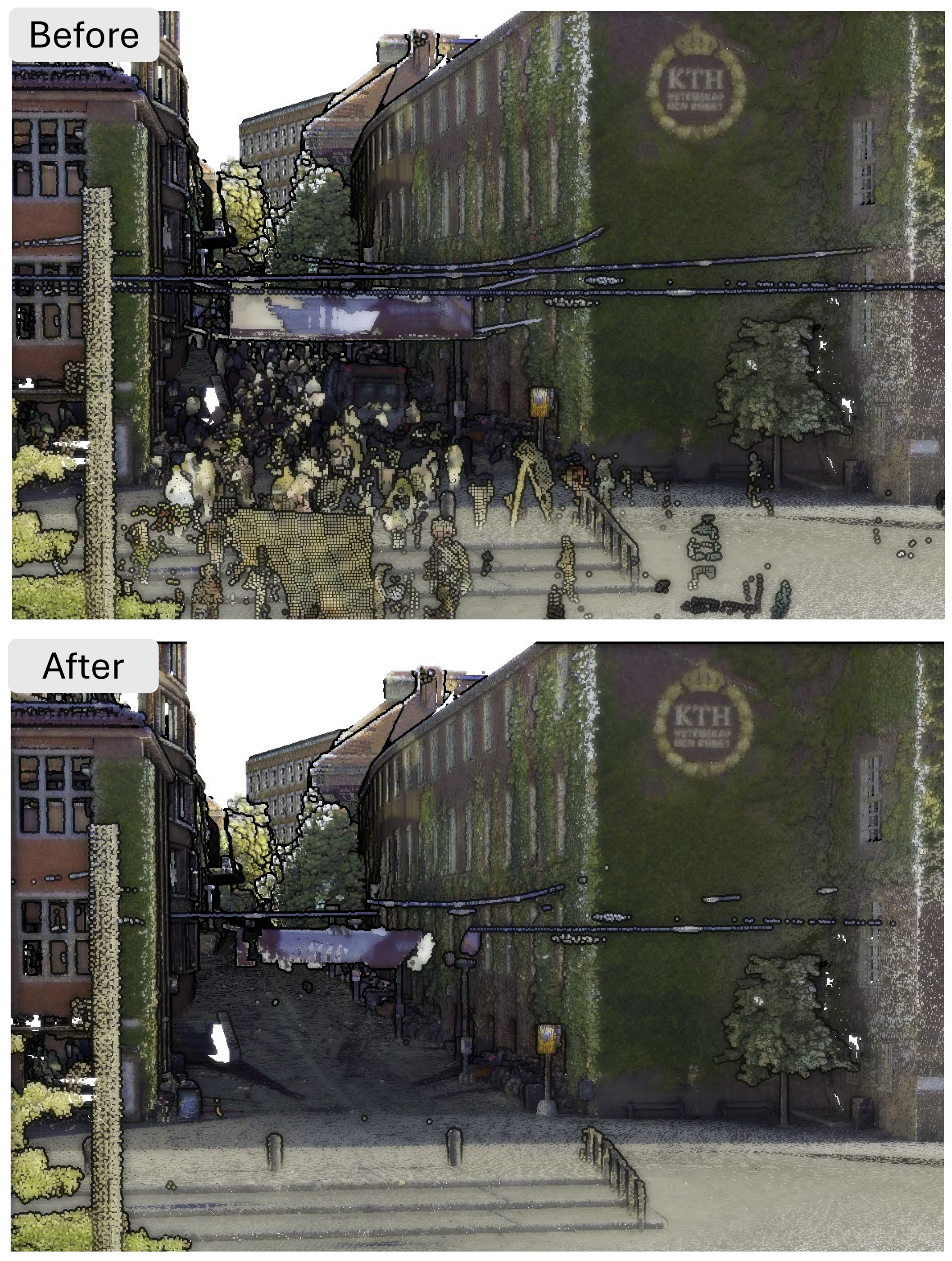



Fig. 4 (a) Point cloud with the real sensor position offset one cell up compared to Fig. 3(a). (b) By increasing the number of neighboring cells that must be intersected or hit to two (i.e., $d_p = 2$) we account for a localization error of up to two voxels in any direction.

## 3. Experiment






Tab. 1: Quantitative comparison of dynamic points removal in point cloud maps. DUFOMap★, results where we query for each new scan online, using the information acquired so far.

| | KITTI small town (00) | | | KITTI highway (01) | | | Argoverse 2 big city | | | Semi-indoor | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Methods | SA ↑ | DA ↑ | AA ↑ | SA ↑ | DA ↑ | AA ↑ | SA ↑ | DA ↑ | AA ↑ | SA ↑ | DA ↑ | AA ↑ |
| Removert [8] | 99.44 | 41.53 | 64.26 | 97.81 | 39.56 | 62.20 | 98.97 | 31.16 | 55.53 | 99.96 | 12.15 | 34.85 |
| ERASOR [9] | 66.70 | 98.54 | 81.07 | 98.12 | 90.94 | 94.46 | 77.51 | 99.18 | 87.68 | 94.90 | 66.26 | 79.30 |
| OctoMap [16] | 68.05 | 99.69 | 82.37 | 55.55 | 99.59 | 74.38 | 69.04 | 97.50 | 82.04 | 88.97 | 82.18 | 85.51 |
| DUFOMap (Ours) | 97.96 | 98.72 | **98.34** | 98.09 | 94.20 | **96.12** | 96.67 | 88.90 | 92.70 | 99.64 | 83.00 | **90.94** |
| Dynablox [17] | 96.76 | 90.68 | 93.67 | 96.33 | 68.01 | 80.94 | 96.08 | 92.87 | **94.46** | 98.81 | 36.49 | 60.05 |
| DUFOMap★ (Ours) | 98.37 | 92.37 | 95.31 | 98.48 | 81.34 | 89.50 | 98.66 | 73.98 | 85.43 | 99.94 | 54.76 | 73.98 |

Tab. 2: **Runtime comparison** of different methods.

| Methods | Run time per point cloud [s] ↓ | |
|---|---|---|
| | KITTI highway | Semi-indoor |
| Removert [8] | 0.134 ± 0.004 | 0.515 ± 0.024 |
| ERASOR [9] | 0.718 ± 0.039 | 0.064 ± 0.011 |
| OctoMap [16] | 2.981 ± 0.952 | 1.048 ± 0.256 |
| Dynablox [17] | 0.141 ± 0.022 | 0.046 ± 0.008 |
| DUFOMap (Ours) | **0.062 ± 0.014** | **0.019 ± 0.003** |

Tab. 4: Ablation study of DUFOMap. $v$ voxel size [m].

| Parameter settings | SA [%] ↑ | DA [%] ↑ | AA [%] ↑ |
|---|---|---|---|
| w/o $d_s$, $d_p$, $v = 0.1$ | 14.89 | 99.99 | 38.58 |
| $d_s = 0.2$, $v = 0.1$ | 30.29 | 99.99 | 55.03 |
| $d_p = 1$, $v = 0.1$ | 91.89 | 98.97 | 95.37 |
| $d_s = 0.2$, $d_p = 1$, $v = 0.2$ | 92.97 | 98.24 | 95.57 |
| $d_s = 0.2$, $d_p = 1$, $v = 0.1$ | 97.96 | 98.72 | **98.34** |

## 4. Conclusion

- We propose, ***DUFOMap***, a method for detecting dynamics by finding parts of space that has been observed as free taking into account **sensor noise and localization errors**.
- Our method achieves **SOTA performance** in both offline and online scenarios across different scenarios and sensors.
- We demonstrate that our method **generalizes** in experiments on datasets with five different sensors using the same setting for the method's three parameters.

Follow us on GitHub: KTH-RPL

Scan me

Not only ***DUFOMap*** but also ***all*** methods we compared.

WASP WALLENBERG AI, AUTONOMOUS SYSTEMS AND SOFTWARE PROGRAM