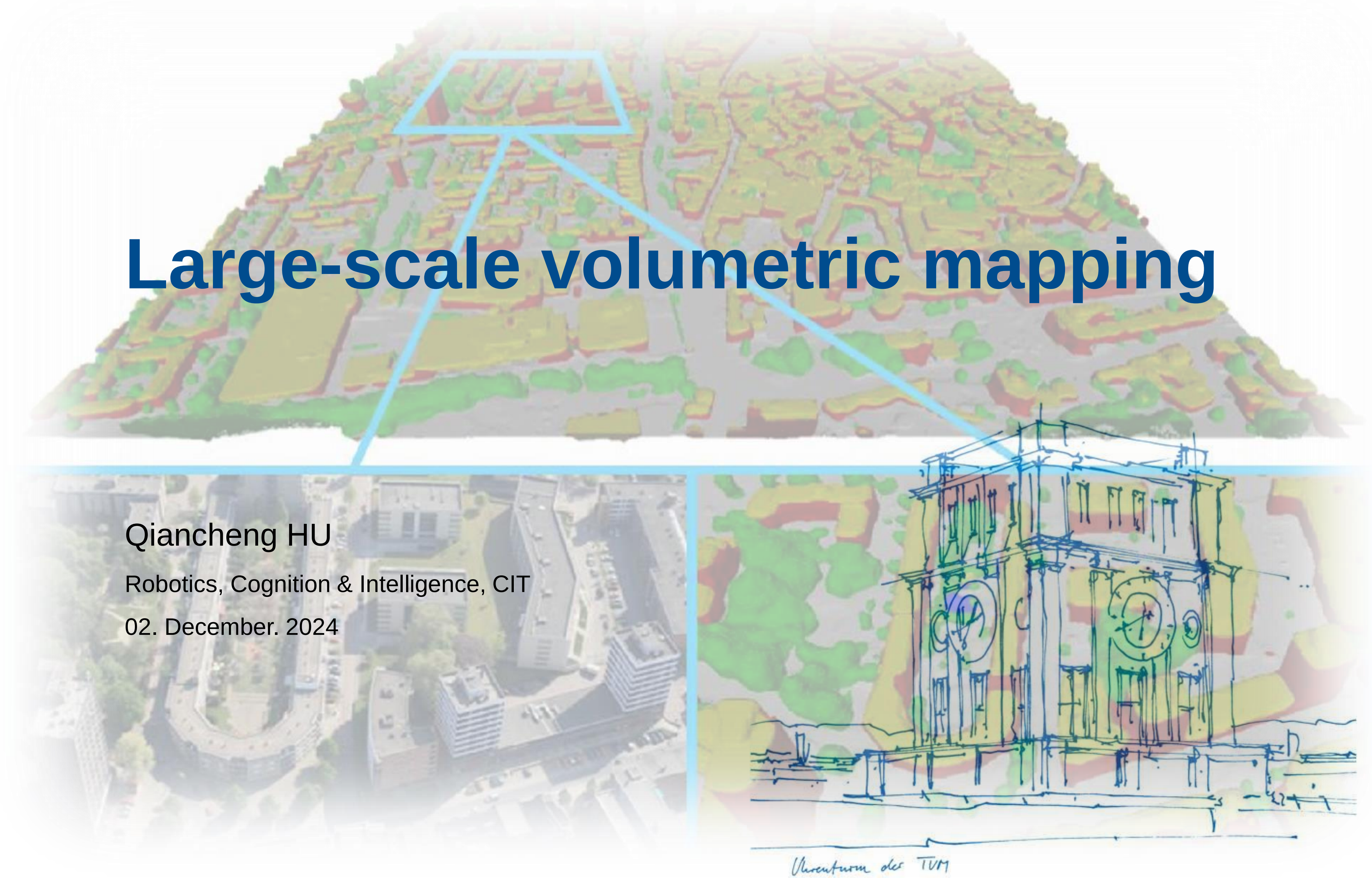

Large-scale volumetric mapping

Qiancheng HU

Robotics, Cognition & Intelligence, CIT

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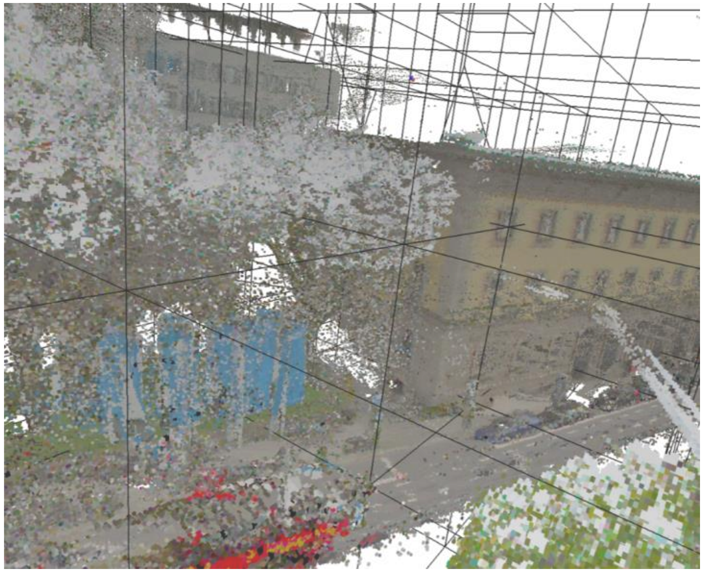
I. Introduction

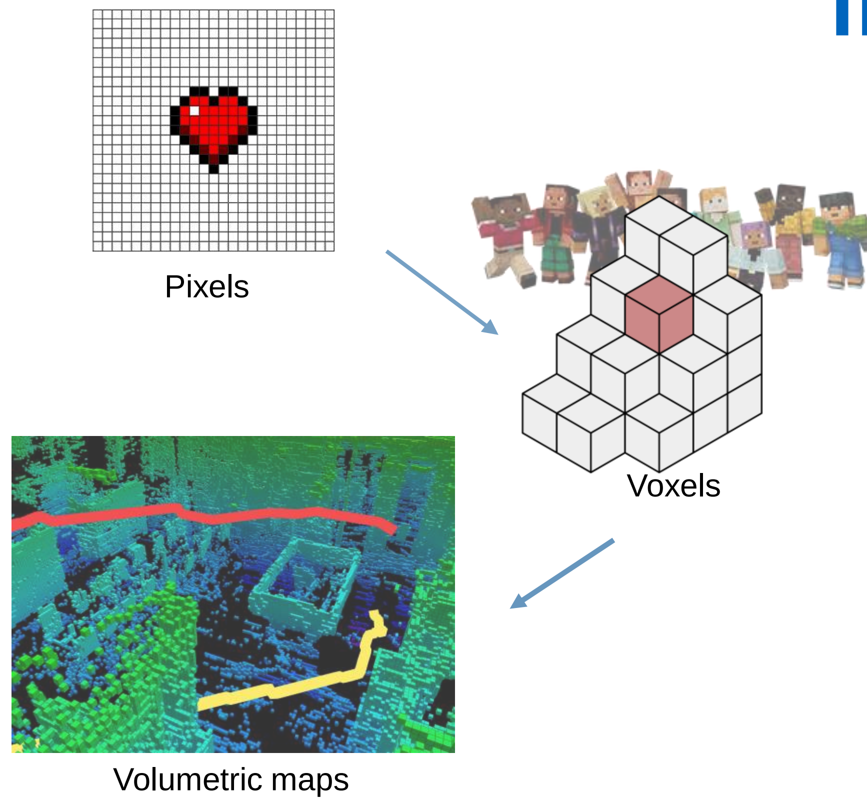
Significance and challenges

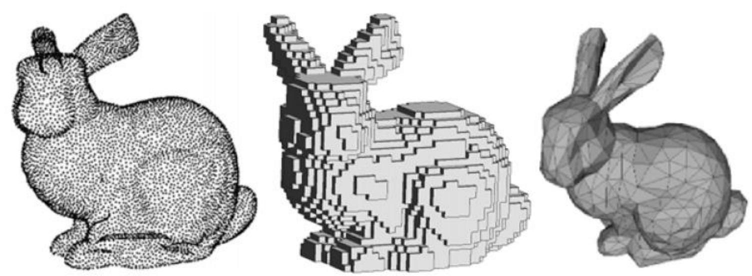
- **Importance of Volumetric Mapping**
- **Challenges at Large Scales**
  - Data Volume
  - Memory Efficiency
  - Global Consistency



Introduction - *Motivation*

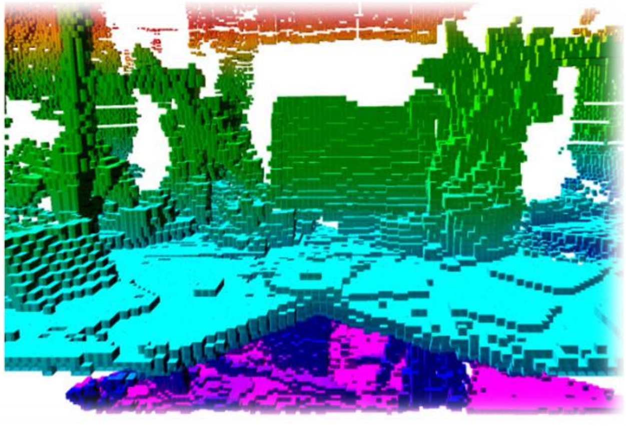
- **Volumetric Mapping with Voxels**:
  - Basis for autonomous systems' environmental understanding.
- **Reduced Computational Complexity**:
  - Compared to point clouds, voxel-based mapping enables efficient processing and storage. (Fixed upper-bound Computational Complexity)
- **Applications**:
  - Autonomous vehicles, drones, robots.
- **Recent Advancements**:
  - Sparse convolutional networks (SpConv) improve voxel grid operations.
- **Real-time Adaptation**:
  - Systems can adjust in real-time for navigation and obstacle avoidance.





Introduction *- Challenges at Large Scales*

- **Data Volume**:
  - LiDAR and RGB-D cameras produce vast data, challenging processing and storage.
- **Memory Efficiency**:
  - Need for advanced data structures (e.g., **Octrees**) to store large maps compactly.
- **Global Consistency**:
  - Alignment errors accumulate over large maps, requiring techniques like loop closure and optimization.



II. Related Works

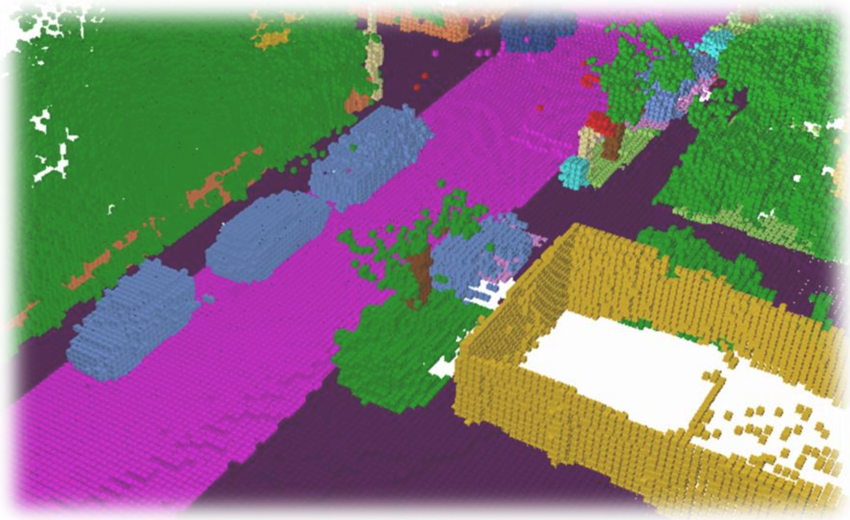
Key advancements in volumetric mapping

Related Work *- Overview*

- **Hierarchical Representations**:
  - Efficient memory management and hybrid compression techniques using Octrees and scalability improvements with OpenVDB.(Hagmanns. 2022, Wurm. 2010, Gehrung. 2016)

- **Semantic Mapping**:
  - Semantic layers enhance map interpretability; (Blaha. 2016)
  - Elastic submaps manage transitions between indoor and outdoor spaces.(Wang. 2022)

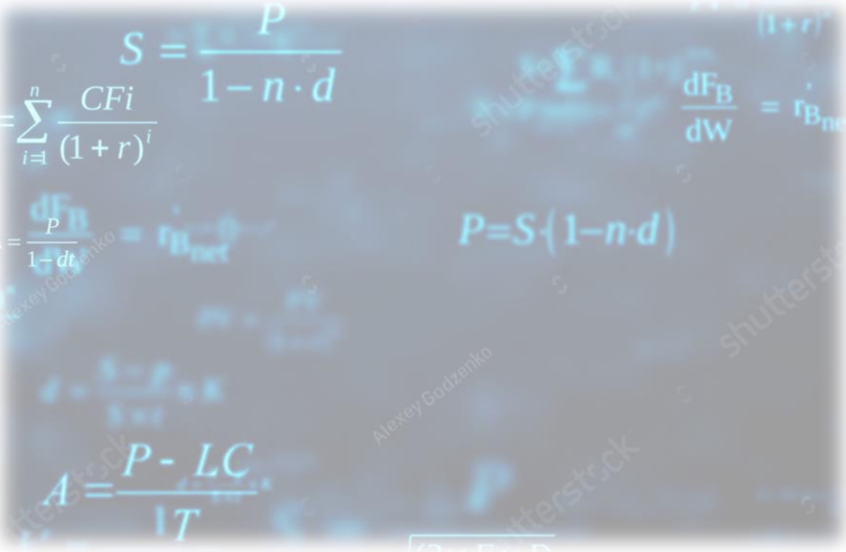
- **Surface Modeling and Global Consistency**: .
  - SDFs and TSDFs improve surface accuracy and reduce alignment errors. (Reijgwart. 2019, Kühner. 2020)



III. Methods

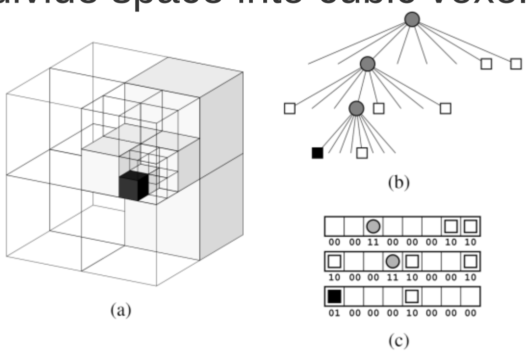
Exploring key techniques to address challenges in volumetric mapping

- **Hierarchical Representations**
- **Surface Modeling**
- **Semantic and Adaptive Frameworks**
- **Global Consistency**



Methods *- Hierarchical Representations*

- **Octrees**
  – divide space into cubic voxels.



- **Log-odds representation**
  – For efficient belief updates. (also enables loop adaption)

$$L(n \mid z_{1:t}) \quad = \quad L(n \mid z_{1:t-1}) + L(n \mid z_t).$$

- **OctoMap framework**
  – optimizes memory by pruning child nodes. (resolution determined by depth of nodes)

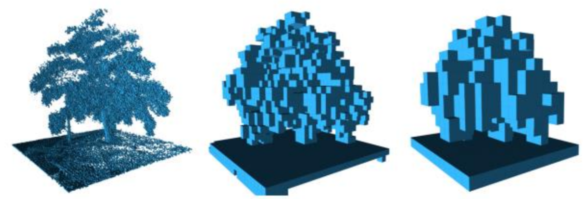
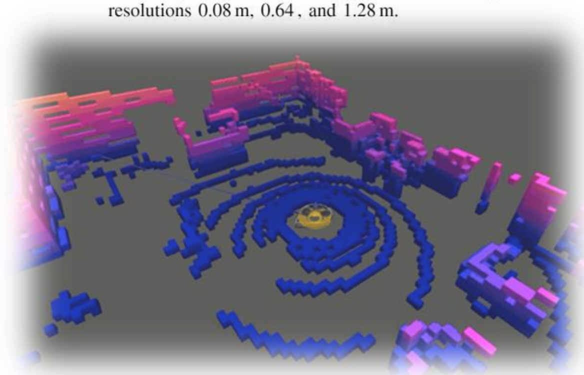
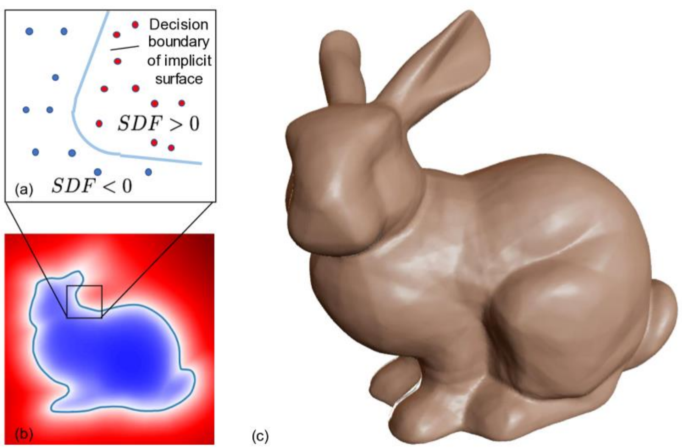


Fig. 3. By limiting the depth of a query, multiple resolutions of the same map can be obtained at any time. The occupied cells are displayed in resolutions 0.08 m, 0.64 , and 1.28 m.



Methods *- Surface Modeling*

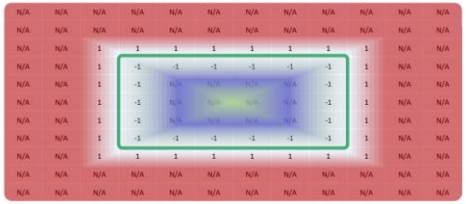
- **SDFs**
  – model surfaces with high accuracy.



- **TSDFs**
  – optimize performance with truncation.

Signed Distance Field

Truncated Signed Distance Field



Methods - *Semantic and Adaptive Frameworks*

- **Adaptive regularization** (Blaha. 2016)
  – prioritizes critical areas.

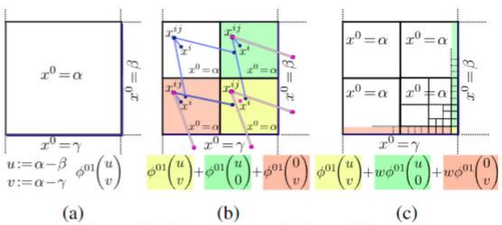


Figure 3: Adaptive regularizer (2D case).

- **Convex energy minimization model**(Blaha. 2016)

$$E(\mathbf{x}) = \sum_{s\in\Omega}\sum_{i} \rho_s^i x_s^i + \sum_{i,j;i<j} \phi^{ij}(x_s^{ij} - x_s^{ji})$$

Discrete Energy in the Octree

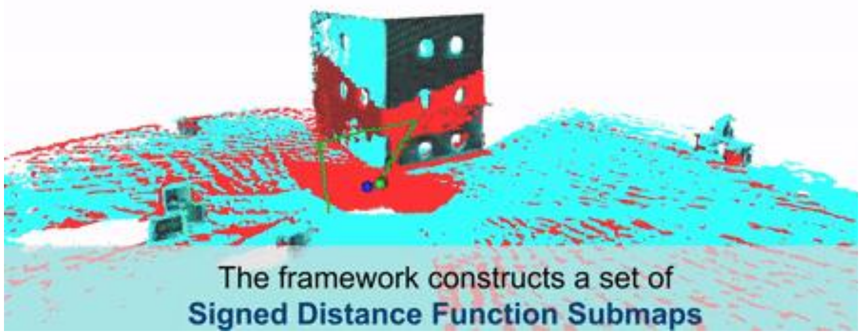
$$E_l(\mathbf{x}_l^*) \geq E_{l+1}(\mathcal{A}_{l,l+1}\mathbf{x}_l^*) \geq E_{l+1}(\mathbf{x}_{l+1}^*)$$

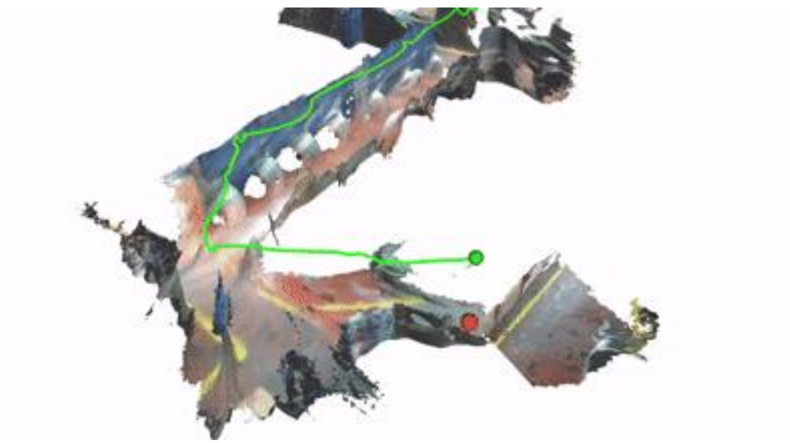
- **Elastic submaps** adjust to environmental changes. (Wang. 2022), based on the work of Voxgraph

![TUM logo]

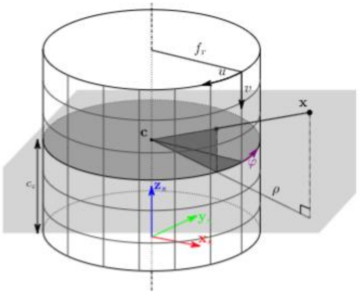
Methods - *Global Consistency*

- **SDF submaps (Reijgwart. 2019)**





- **LiDAR-based fusion (Kühner. 2020)**
  - Cylinder projection model



  - Loop closure weight updates

$$F(\mathbf{x})_i = \frac{W(\mathbf{x})_{i-1}F(\mathbf{x})_{i-1} + w(\mathbf{x})f(\mathbf{x})}{W(\mathbf{x})_{i-1} + w(\mathbf{x})}$$

$$W(\mathbf{x})_i = W(\mathbf{x})_{i-1} + w(\mathbf{x}).$$

$$T_{\text{loop}} = \arg\min_{T} \sum_{i=0}^{n-2} \|\Delta t_i - \Delta t_i^{\text{odom}}\|^2 + \beta \sum_{(T_s,T_d)\in L} \|t_s - t_d\|^2$$

IV. Experiments and Results

Real-world evaluations

- **Memory Efficiency**
- **Semantic benchmarks**
- **Global Consistency**

Experiments and Results - *Memory Efficiency*

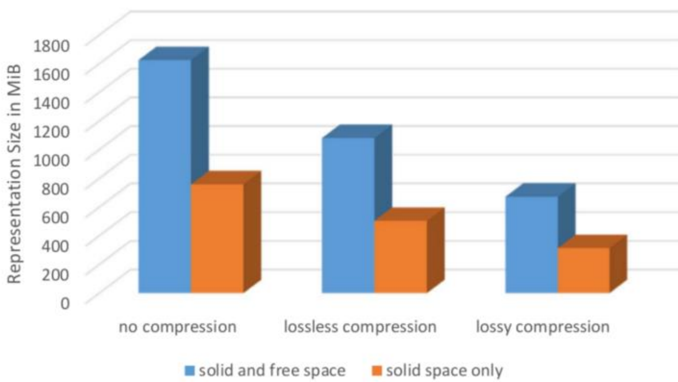
- **OctoMap (Wurm. 2010)**

TABLE I

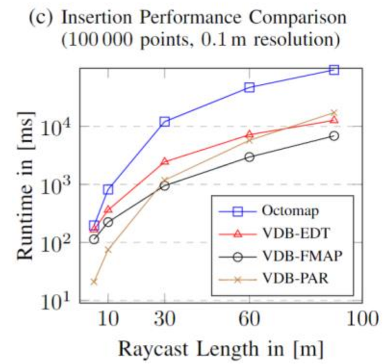
MEMORY CONSUMPTION OF VARIOUS 3D DATASETS

Map dataset	Mapped area [m^3]	Resolution [m]	Memory consumption [MB] Full grid	No compression	Lossless compression	File size [MB] All data	Binary
Small scale indoor	$3.5 \times 5.2 \times 1.7$	0.05	1.03	1.91	1.38	0.54	0.02
FR-079 corridor	$43.8 \times 18.2 \times 3.3$	0.05	80.54	73.64	41.70	15.80	0.67
		0.1	10.42	10.90	7.25	2.71	0.14
Freiburg outdoor	$292 \times 167 \times 28$	0.20	654.42	188.09	130.39	49.75	2.00
		0.80	10.96	4.56	4.13	1.53	0.08
New College (Epoch C)	$250 \times 161 \times 33$	0.20	637.48	91.43	50.70	18.71	0.99
		0.80	10.21	2.35	1.81	0.64	0.05

- **Map compression (Gehrung. 2016)**



- **Global occupancy mapping using OpenVDB(Hagmanns. 2022)**



Experiments and Results - *Semantic Mapping*

- **Adaptive resolution framework(Blaha. 2016)**

Scene	Runtime@0.4 m [sec] 1	2	3	4	Memory@0.4 m [GB] 1	2	3	4	Memory@0.2 m [GB] 3	4
Octree	19883	19672	5488	4984	2.7	2.6	0.7	0.7	3.3	2.7
Grid	430545	416771	91982	92893	54.3	54.3	13.6	13.6	108.5	108.5
Octree (naive)	43174	43845	10603	11343	6.5	6.8	1.7	1.9	—	—
Ratio (Grid)	**21.7**	21.2	16.8	18.6	20.1	**20.9**	19.4	19.4	32.9	**40.2**
Ratio (Octree naive)	2.2	2.2	1.9	2.3	2.4	2.6	2.4	2.7	—	—

Table 2: Comparison of run-time and memory footprint of our method (*Octree*), [17] (*Grid*), and a *naive Octree*. Maximum gains for processing time and memory consumption per refinement level are shown in bold. The target *Grids* feature a resolution of *512 x 512 x 256* (Scene 1 and 2) and *256 x 256 x 256* (Scene 3 and 4) at 0.4 m.

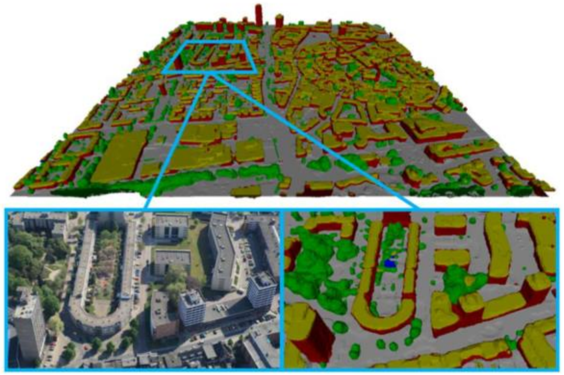


Figure 1: Semantic 3D model of the city of Enschede generated with the proposed adaptive multi-resolution approach.

- **Elastic submaps framework(Wang. 2022)**

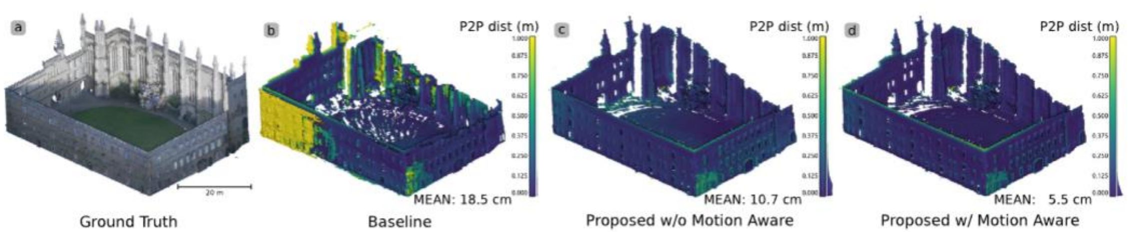


Fig. 9. Exp 4.1 – The comparison between (**a**) the ground truth map of NCD Long experiment and each reconstruction created by (**b**) the baseline, (**c**) the proposed system without motion aware LiDAR integration and (**d**) the proposed system with motion aware LiDAR integration. Colours indicate point-to-point distances (P2P dist) between each reconstruction and the ground truth, and the distributions are also presented beside the colour bar. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Experiments and Results - *Global Consistency*

- **Voxgraph(Reijgwart. 2019)**

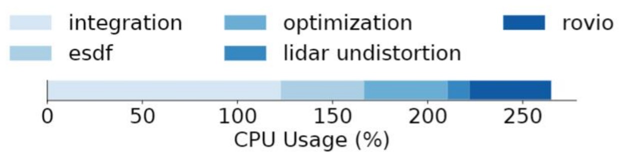
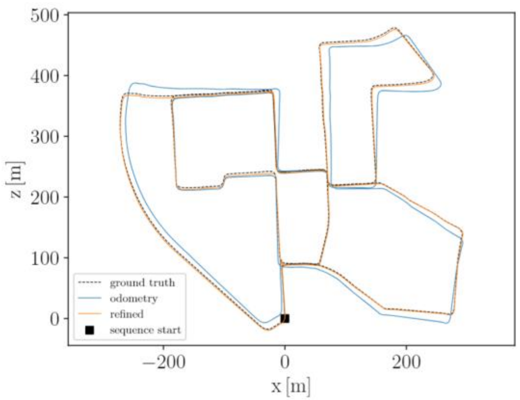
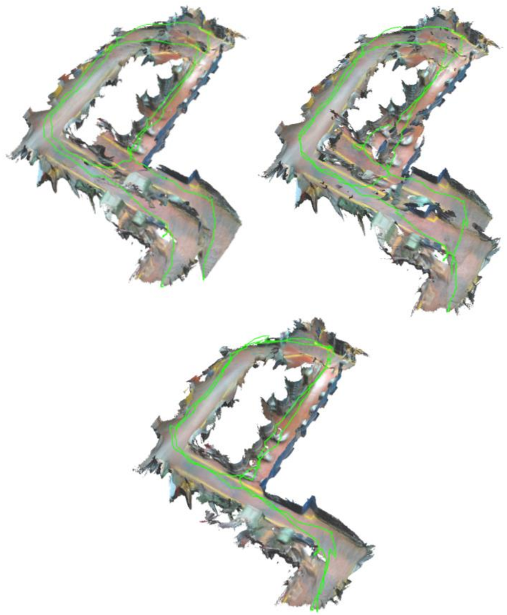


Fig. 6: A breakdown of *voxgraph* CPU usage during a typical MAV flight from Sec. VIII-B. The global optimization scheme suggested in this proposal consumes 44% of a single CPU core.

- **LiDAR fusion(Kühner. 2020)**



  - Adjusting trajectory errors on the odometry



- Comparing with- and without SDF submaps

Experiments and Results - *Discussion of Trade-offs*

- **Memory Efficiency vs. Precision:**
  - OctoMap is fast for large environments
  - Gehrung's method balances efficiency with accuracy

- **Real-time Adaptability vs. Computational Cost**
  - Static solutions (Blaha. 2016) cannot adapt as quickly to fast-changing environments
  - Alternatives such as Octomap-RT(Min. 2023) though results not presented here, does solve the problem, but relies on computational expensive devices(GPU).

IV. Future Works

Proposed research directions

Key Aspects

- ❑ **Real-Time Scalability**
- ❑ **Sensor Fusion Integration**
- ❑ **Memory Efficiency**
- ❑ **Semantic Integration**

Possiple Directions

- ❑ **Semantic and Dynamic Adaptability**
- ❑ **GPU-Accelerated Volumetric Mapping**
- ❑ **Advanced hybrid Compression Techniques**
- ❑ **Multi-Sensor Fusion**
- ❑ **Global Consistency & Trajectory Optimization**

V. Summary

…To wrap up…

Volumetric Mapping

Challenges

…

Key Methods

…

Experiments

…

References

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Thanks for your attention!