

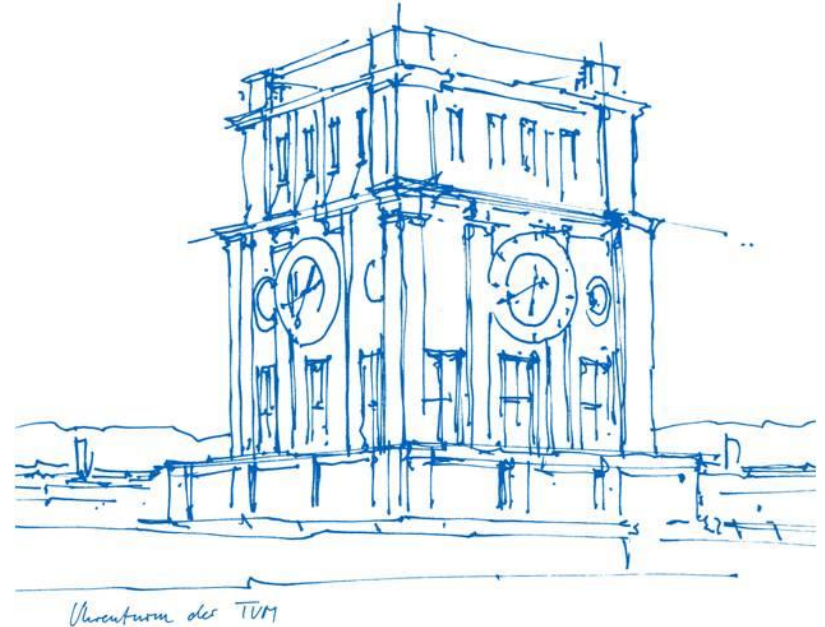
# Monocular Camera Localization in 3D LiDAR Maps

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Vision-based Navigation

Garching b. München, 24. July 2023



# Introduction

Goal: Localize the monocular camera in a 3D LiDAR Map

- Input: Image stream + 3D point cloud map
- Output: Estimated camera pose trajectory

Method: Align the reconstructed point to 3D LiDAR Map

- Alignment by matching geometry
- Eliminate the accumulated drift

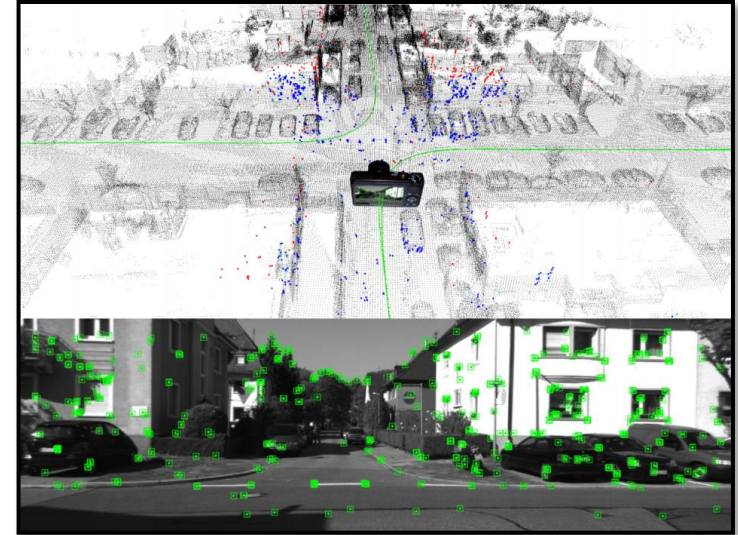
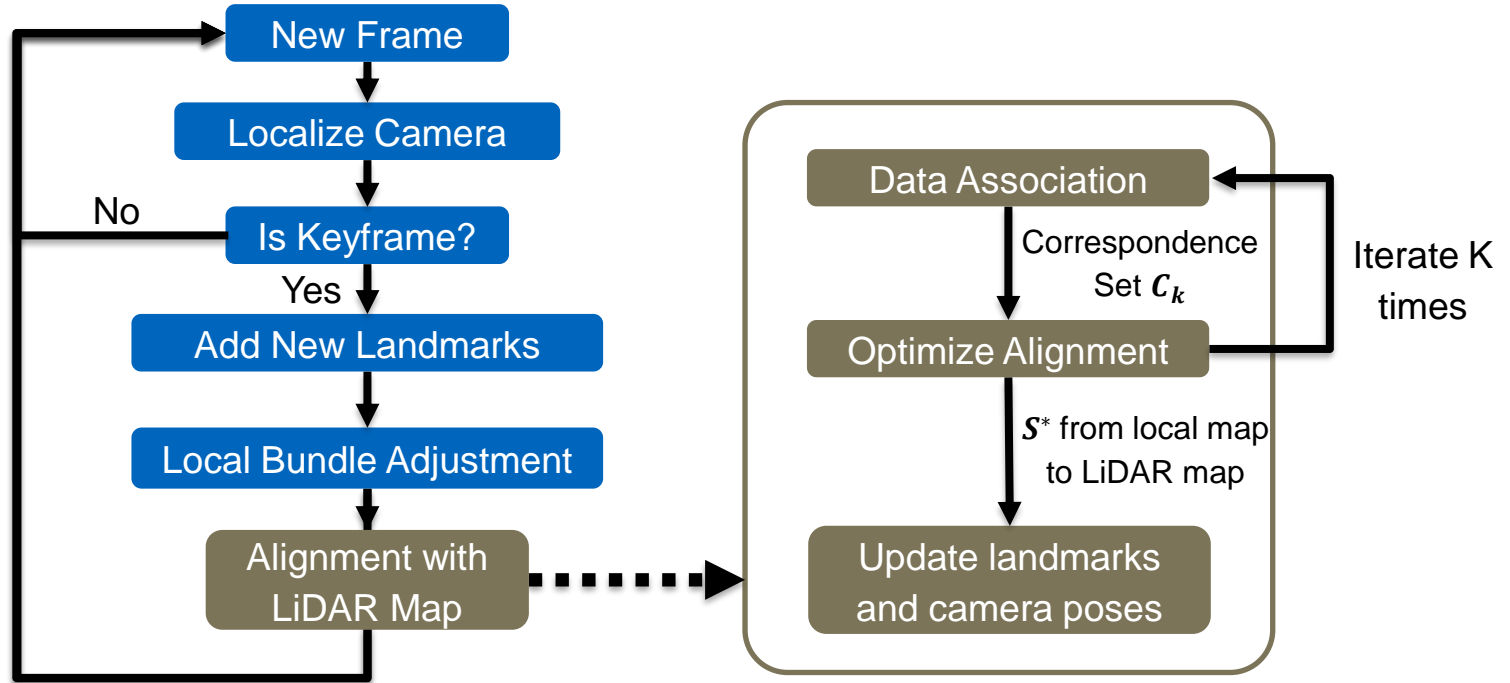


Figure 1: Caselitz, et al. "Monocular Camera Localization in 3D LiDAR Maps."

# Visual Odometry

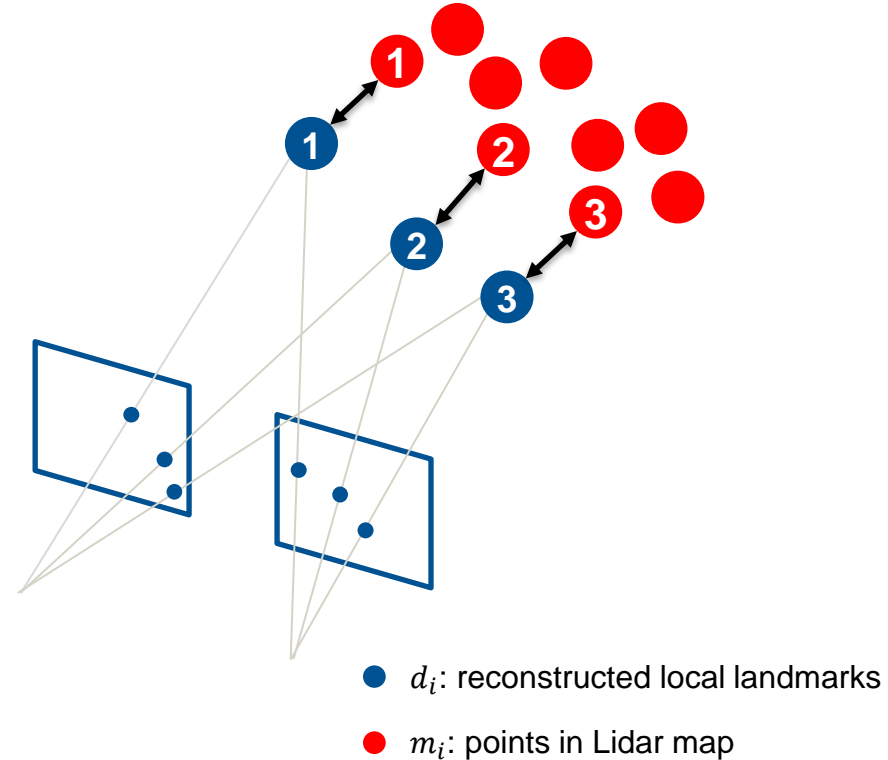


# Alignment-Data Association

- Find correspondences between **reconstructed points** and **points in Lidar map** iteratively

$$\mathcal{C}_k = \{(\mathbf{d}_i, \mathbf{m}_j) \mid \forall \mathbf{d}_i \in \mathcal{D} \mid \exists \underset{\mathbf{m}_j \in \mathcal{M}}{\operatorname{argmin}} \|\mathbf{d}_i - \mathbf{m}_j\|_2 < \tau_k\}.$$

Local landmark
LiDAR point
Distance threshold



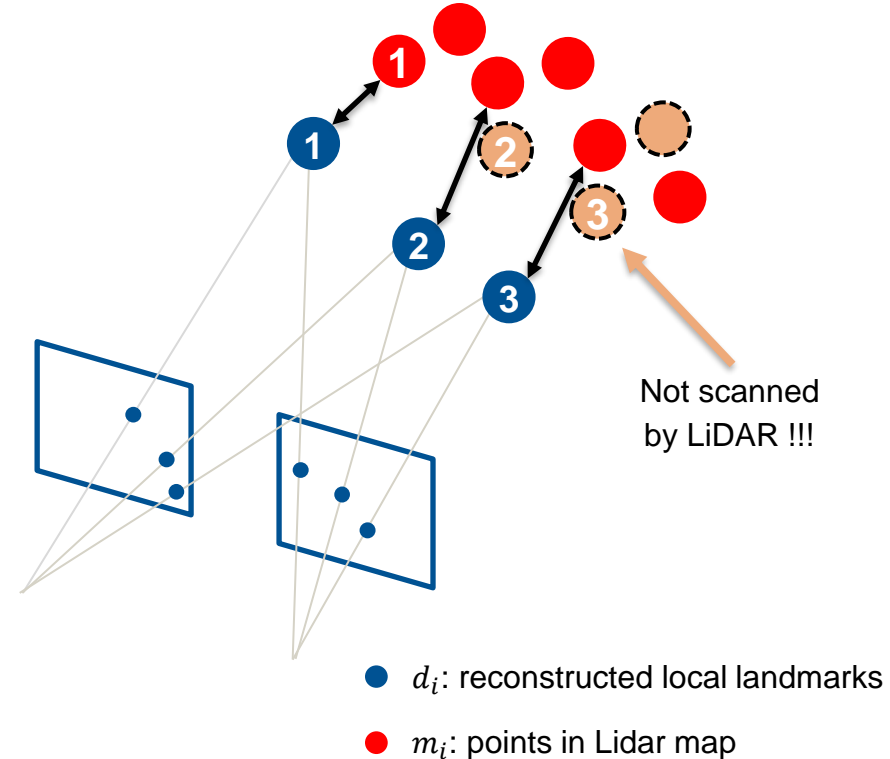
# Alignment-Data Association

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Local landmark
LiDAR point
Distance threshold

Drawback:  
the set of reconstructed points overlaps ***only partially*** with the LiDAR map



# Alignment-Local Point Distribution

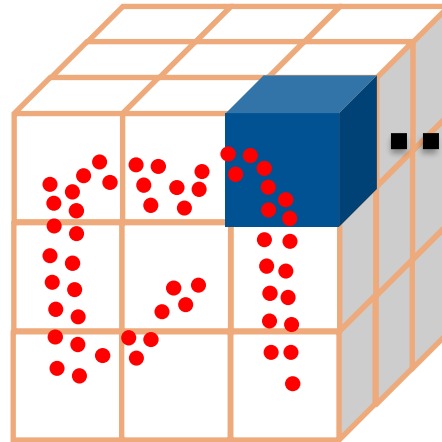
## Preprocessing

- Voxelize the point cloud map
- Use PCA to determine the local point distribution in each voxel

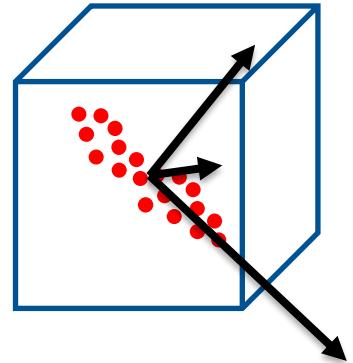


3D Point Cloud Map

Voxelize  
→



Voxelized Map



One Voxel in the Map

# Alignment-Filter out bad correspondence

Good Conditions:

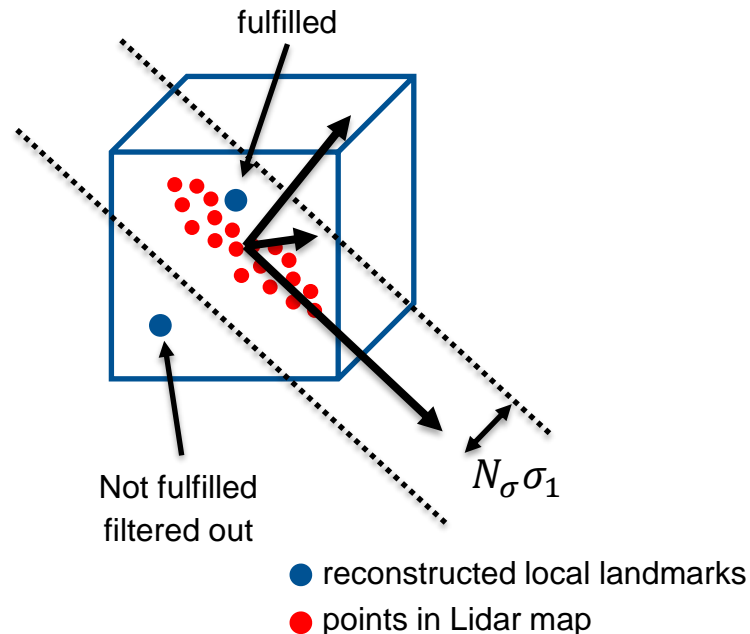
- The amount of **LiDAR points** in a voxel is sufficient

$$N \geq N_{min}$$

- The **reconstructed local landmark** lies inside a multiple standard deviation along the voxel's principle component axes

$$Td_i \leq N_\sigma \sigma$$

- Or any neighboring voxel fulfills above criteria



# Alignment-Optimization

Given a set of correspondences  $\mathcal{C}'_k = \{(d_1, m_1), (d_2, m_2), \dots\}$

Estimate similarity transformation  $S_k^*$  from local reconstruction to LiDAR map

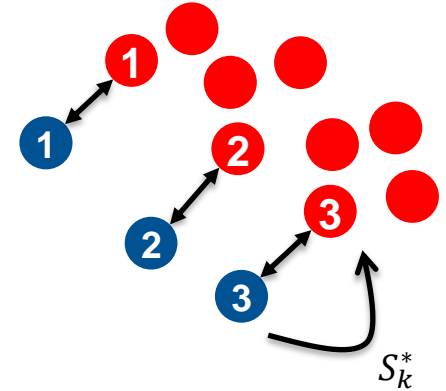
Perform with an ICP scheme

- Update the correspondence set  $\mathcal{C}'_k$  based on current  $S_k^*$  over  $K$  iterations.
- Reduce the distance threshold  $\tau_k$  over  $K$  iterations.

$$\tau_k = -\frac{\tau_{max} - \tau_{min}}{K}k + \tau_{max}.$$

- Error function is squared Euclidean distance between corresponding points

$$e_{Data}(\mathbf{S}, \mathbf{d}_i, \mathbf{m}_j) = \xi(\mathbf{S}\tilde{\mathbf{d}}_i) - \mathbf{m}_j.$$





# Alignment-Optimization

ICP scheme

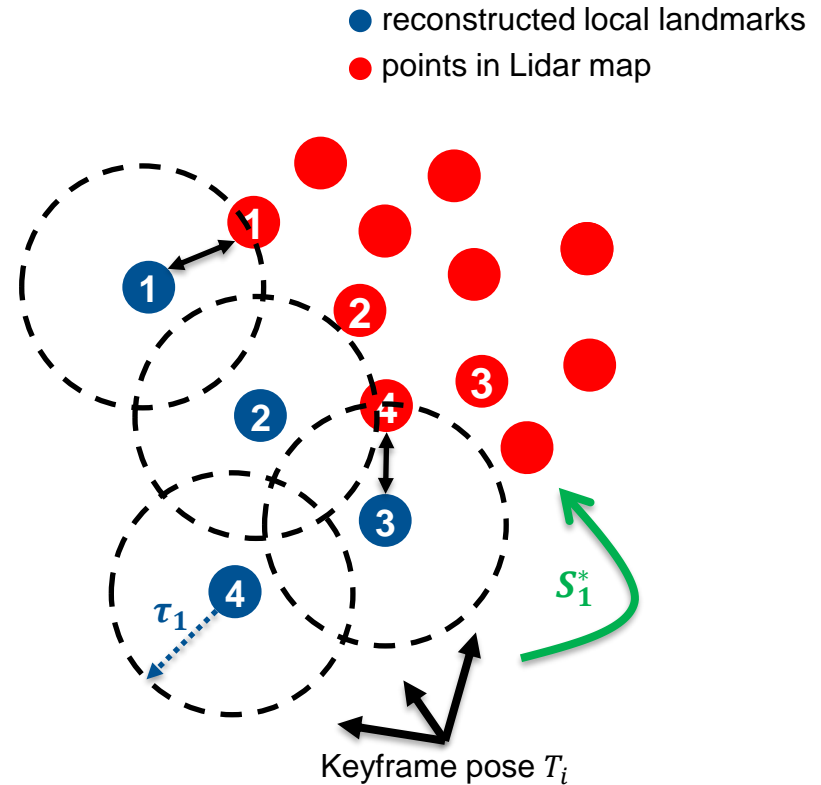
$k=1$

Data Association:

$$C'_k = \{(d_1, m_1), (d_3, m_4)\}$$

Optimization:

Estimate  $s_1^*$



# Alignment-Optimization

ICP scheme

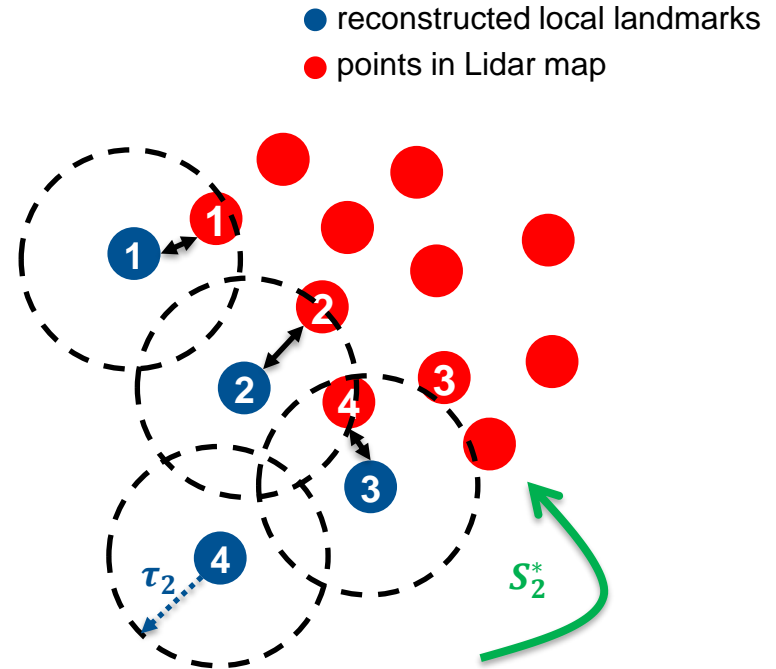
$k=2$

Data Association:

$$C'_k = \{(d_1, m_1), (d_2, m_2), (d_3, m_4)\}$$

Optimization:

Estimate  $s_2^*$



# Alignment-Optimization

ICP scheme

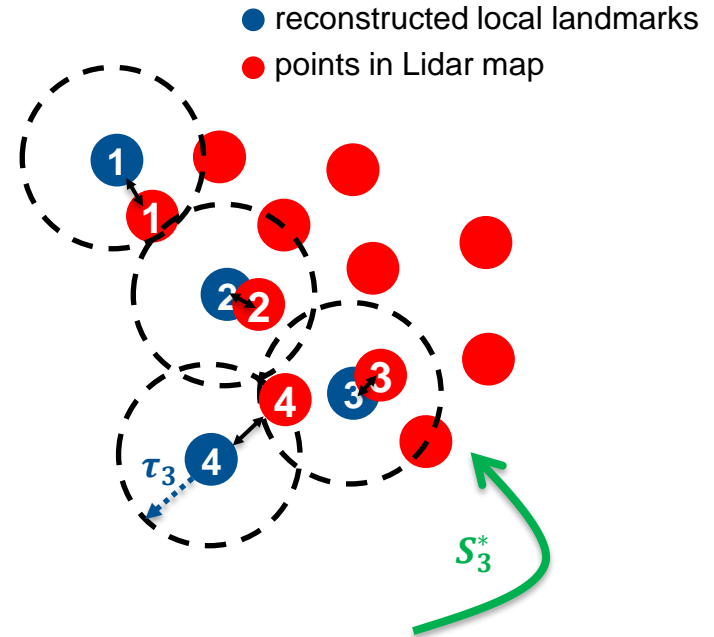
$k=3$

Data Association:

$$C'_k = \{(d_1, m_1), (d_2, m_2), (d_3, m_3), (d_4, m_4)\}$$

Optimization:

Estimate  $s_3^*$



# Alignment-Update landmarks and poses

After K iterations

$$C'_k = \{(d_1, m_1), (d_2, m_2), (d_3, m_3), (d_4, m_4)\}$$

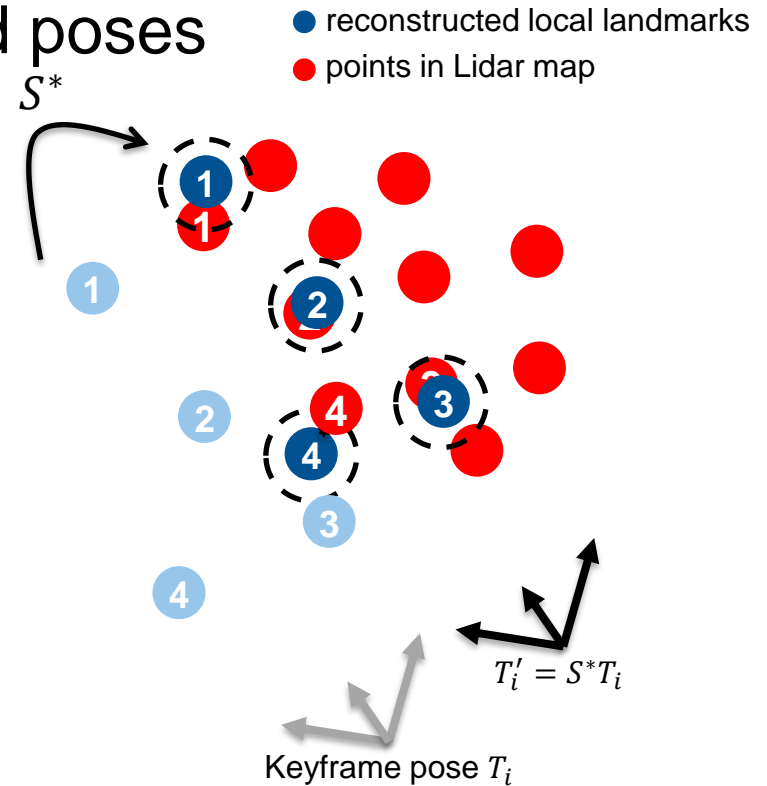
From origin landmarks to optimized landmarks:

$$S^* = \prod_{k=0}^{K-1} S_{K-k}^*$$

Transform all point positions  $d_i$  and keyframe poses  $T_i$

$$D' = \{d'_i = S^* d_i, \forall d_i \in D\}$$

$$T' = \{T'_i = S^* T_i, \forall T_i \in T\}$$



## Result-Stereo Camera for Euroc V1\_01\_easy



Stereo without alignment  
1 min 23 s (~30Hz)

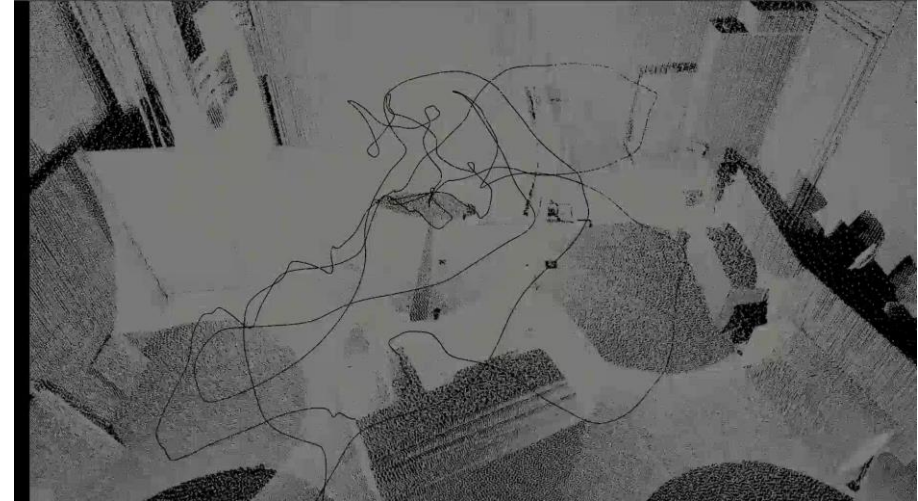


Stereo with alignment  
3 min 53 s (~12Hz)

# Result-Monocular Camera for Euroc V1\_01\_easy



Monocular without alignment  
1 min 09 s (~40Hz)



Monocular with alignment  
2 min 57 s (~15Hz)

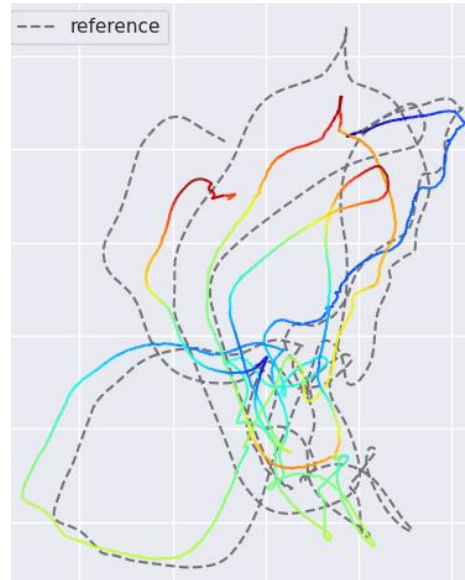
# Result for V1\_01\_easy



Stereo



Stereo + LiDAR map

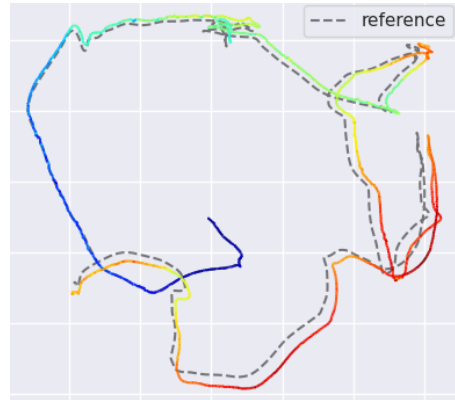


Monocular

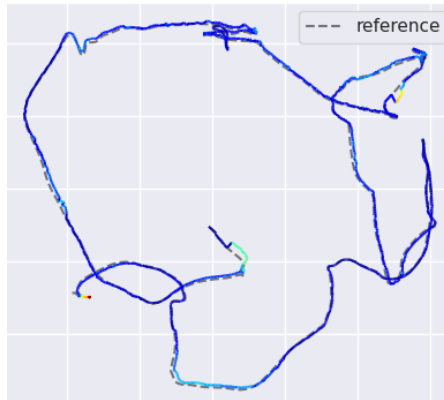


Monocular + LiDAR map

# Result for V2\_01\_easy



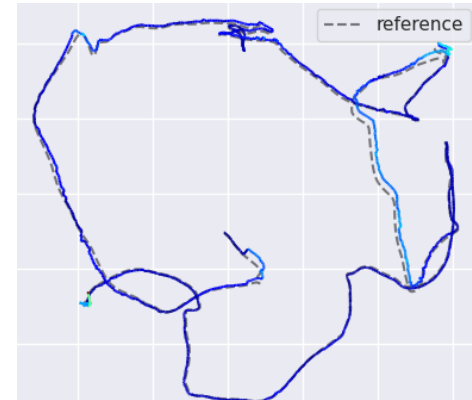
Stereo



Stereo + LiDAR map



Monocular

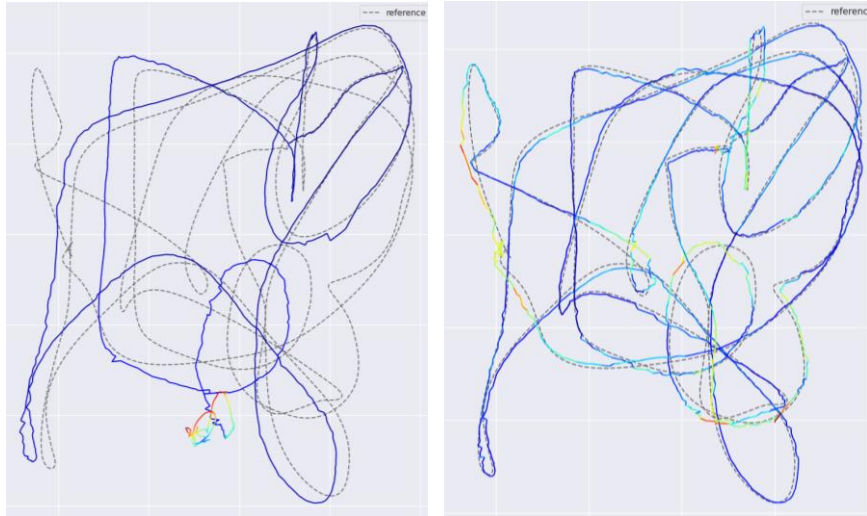


Monocular + LiDAR map



# Other good results

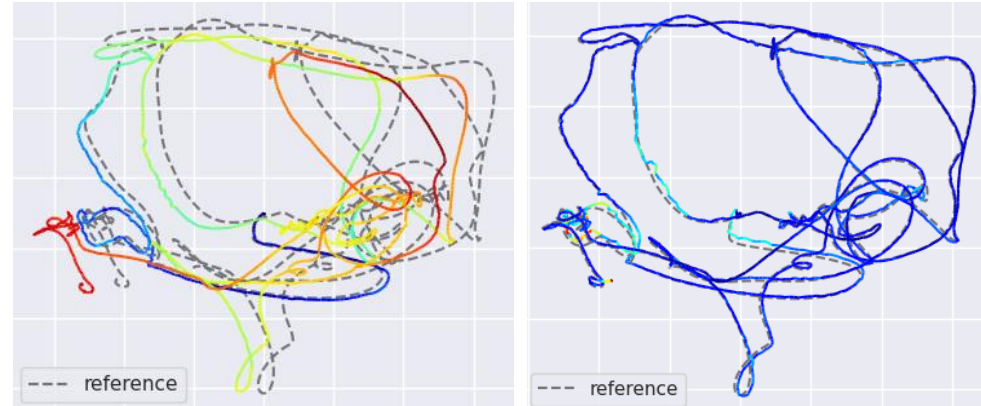
V1\_02\_medium



Monocular

Monocular + LiDAR map

V2\_02\_medium

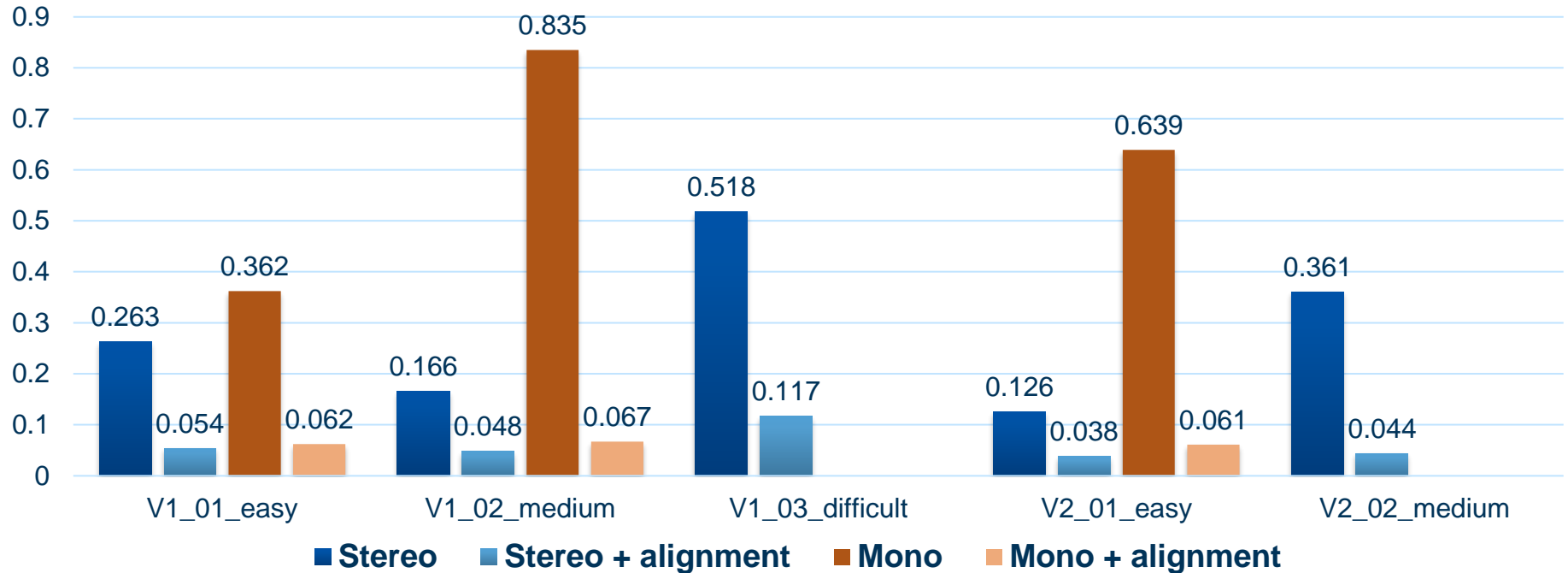


Stereo

Stereo + LiDAR map

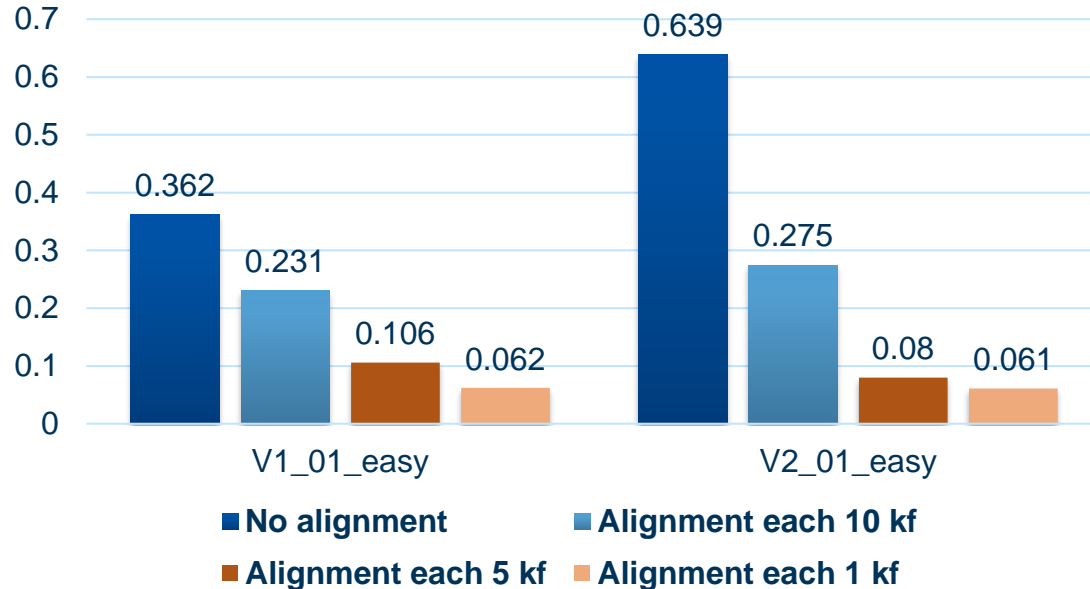
# Result

## APE w.r.t translational part (best in 5 eval)



# Ablation Study-Frequency of alignment

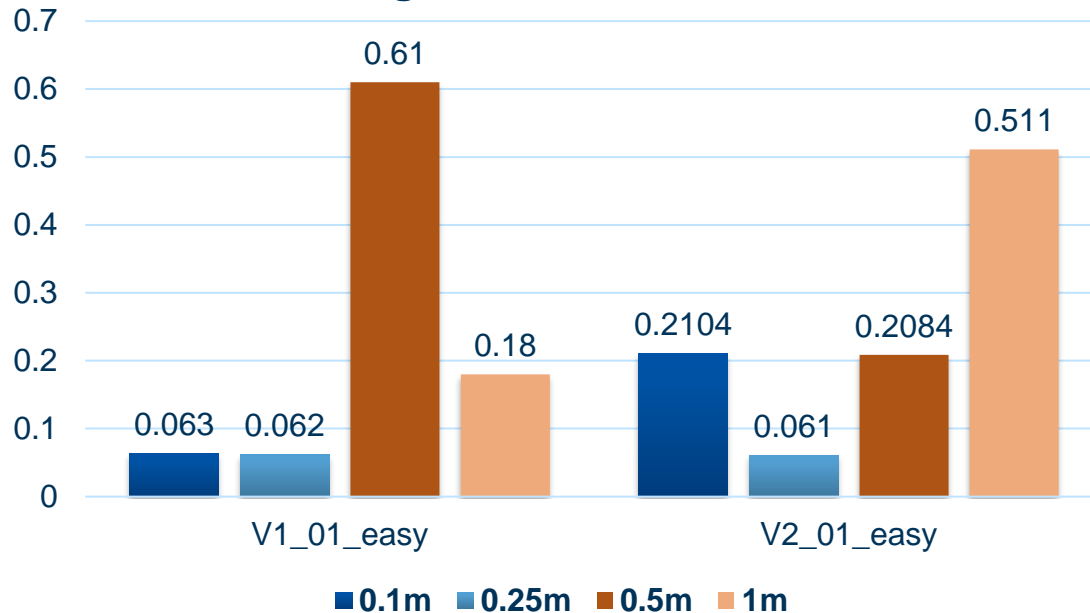
**APE w.r.t translational part (best in 5 eval)**  
**Using Monocular Camera**



- More alignments leads to better performance
- Also leads to more running time!

# Ablation Study-Voxel Size

APE w.r.t translational part (best in 5 eval)  
Using Monocular Camera



- Voxel size is highly **scene-specific**
- **Trade-off** between voxel size and running time

# KITTI Attempt

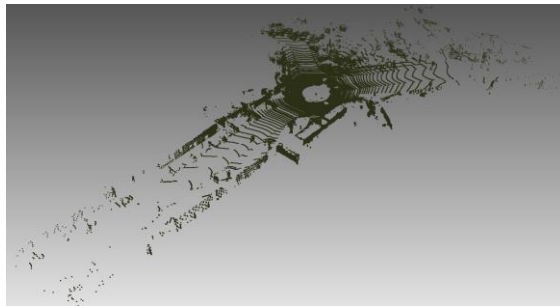
**Euroc:** LiDAR map of the whole scene (~100 Mb/scene)

**KITTI:** Each frame has a LiDAR map (.bin file) (~10 Gb/scene)

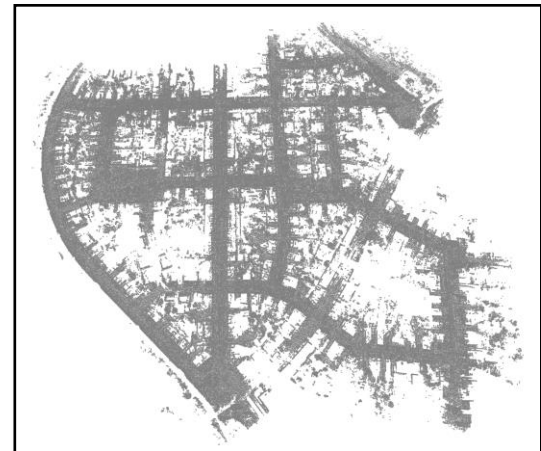
Using downsample to preprocess a map for whole scene



data.ply for one Euroc Scene

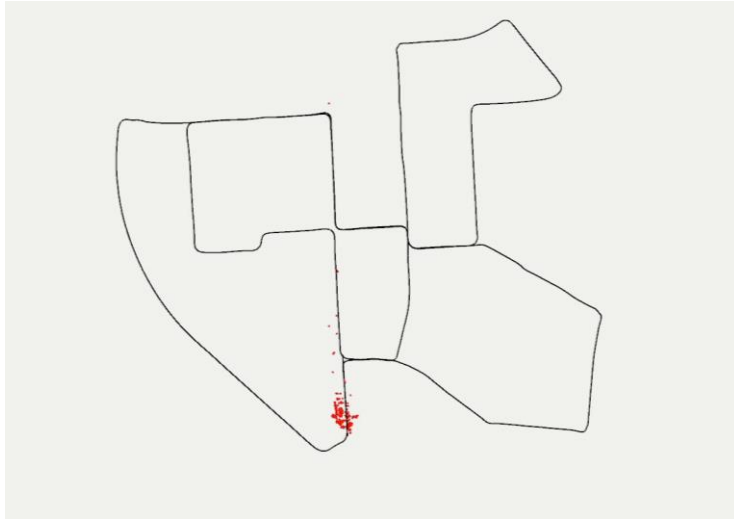


000000.bin in KITTI Sequence (~130k points)

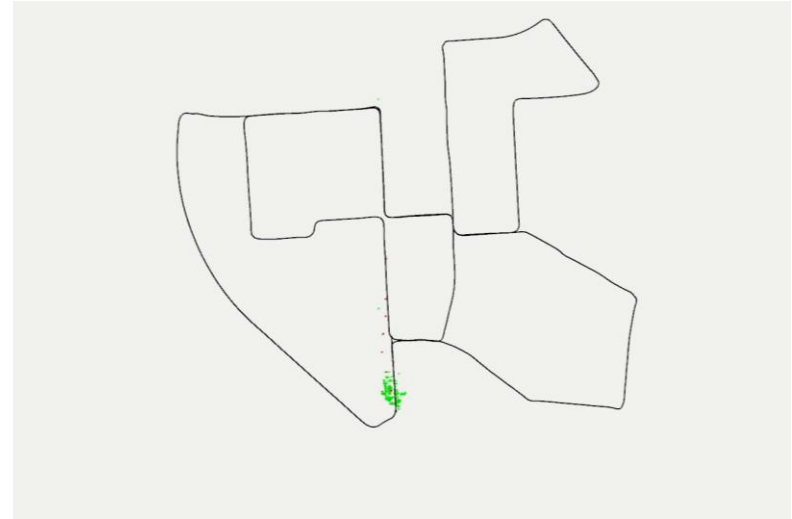


Our LiDAR Map for whole scene

# KITTI Attempt-Result



Stereo



Stereo + whole LiDAR map

# Summary

## Contribution

- Alignment with LiDAR map can **eliminate the accumulated drift**
- Matching based on geometry is **robust to light changes**
- The alignment performance is still **restricted by the based VO performance**

## Improvement potential

- Powerful **CPU**
- Accurate **LiDAR Map**
- Powerful **based VO**

Thanks for your attention!



# Additional Materials

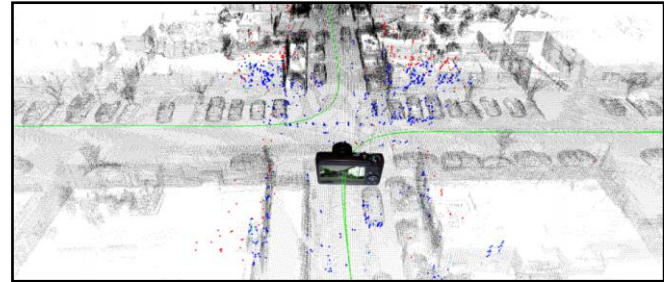
# KITTI-Attempt

## Paper's method

- Use a LIDAR-based SLAM system to get GT trajectory (for loop closure)
- Build a map at resolution of 20 cm

## Our method

- Preprocess a LiDAR map for whole scene
  - Put point clouds for all frames together
  - Downsample
  - Build a map at resolution of 50cm



Paper's LiDAR Map for whole scene



Our LiDAR Map for whole scene