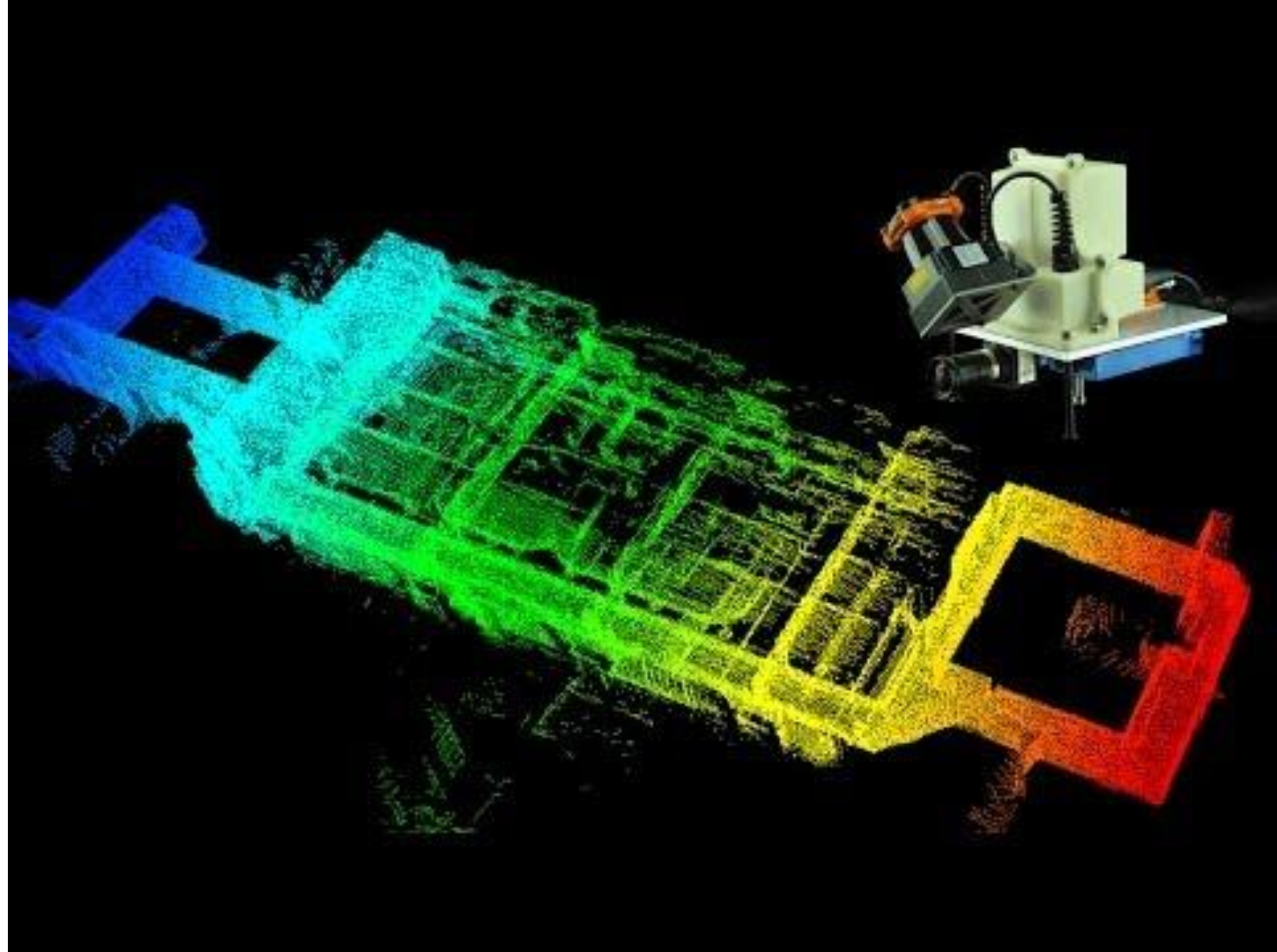


# VLOAM - Visual-Lidar Odometry And Mapping

16-833: Robot Localization and Mapping

Spring 2021

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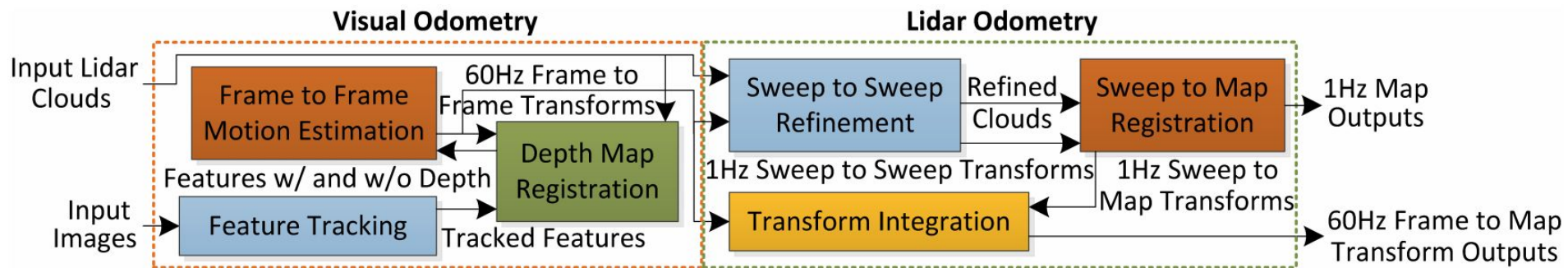
# VLOAM Overview

- Related work
- Software system
- Visual odometry
- Lidar odometry
- Experiments

# Related Work

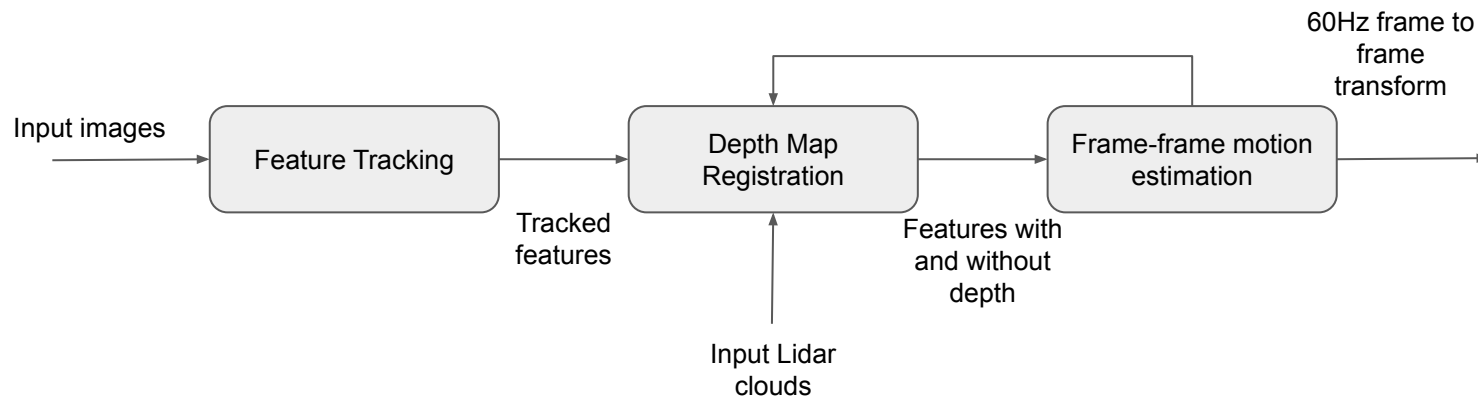
- **Depth for image pixels**
  - Similar to [Engelhard et al., 2011] and [Whelan et al., 2013] using visual images with additional depth
- **Motion recovery**
  - Different from [Scherer et al., 2012] and [Droeschel et al., 2014] where multiple cameras are employed
- **State estimation and map building**
  - Different from [Bosse and Zlot, 2012] and [Zlot and Bosse, 2014] who showed state estimation with 3D lidars alone
- **Visual and lidar odometry performed separately**
  - VO from [Zhang et al., 2014] and LO from [Zhang and Singh 2014]

# Software System



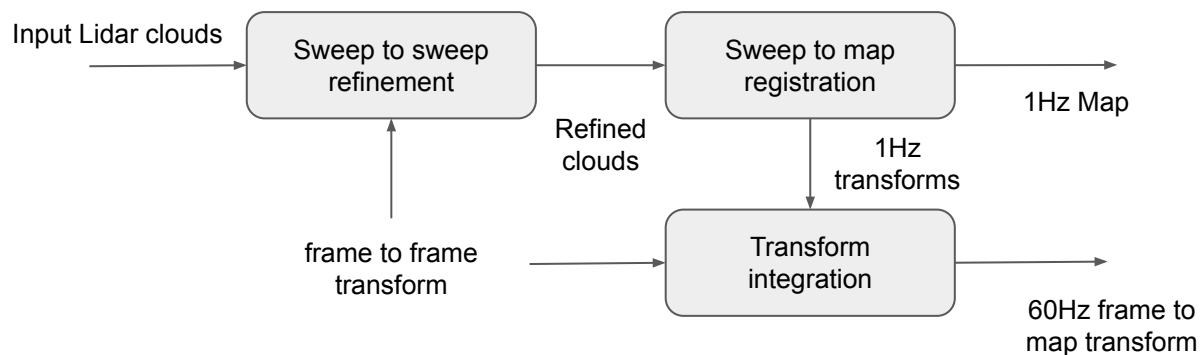
# Software System

## *Visual Odometry*



# Software System

## *Lidar Odometry*



# Visual Odometry



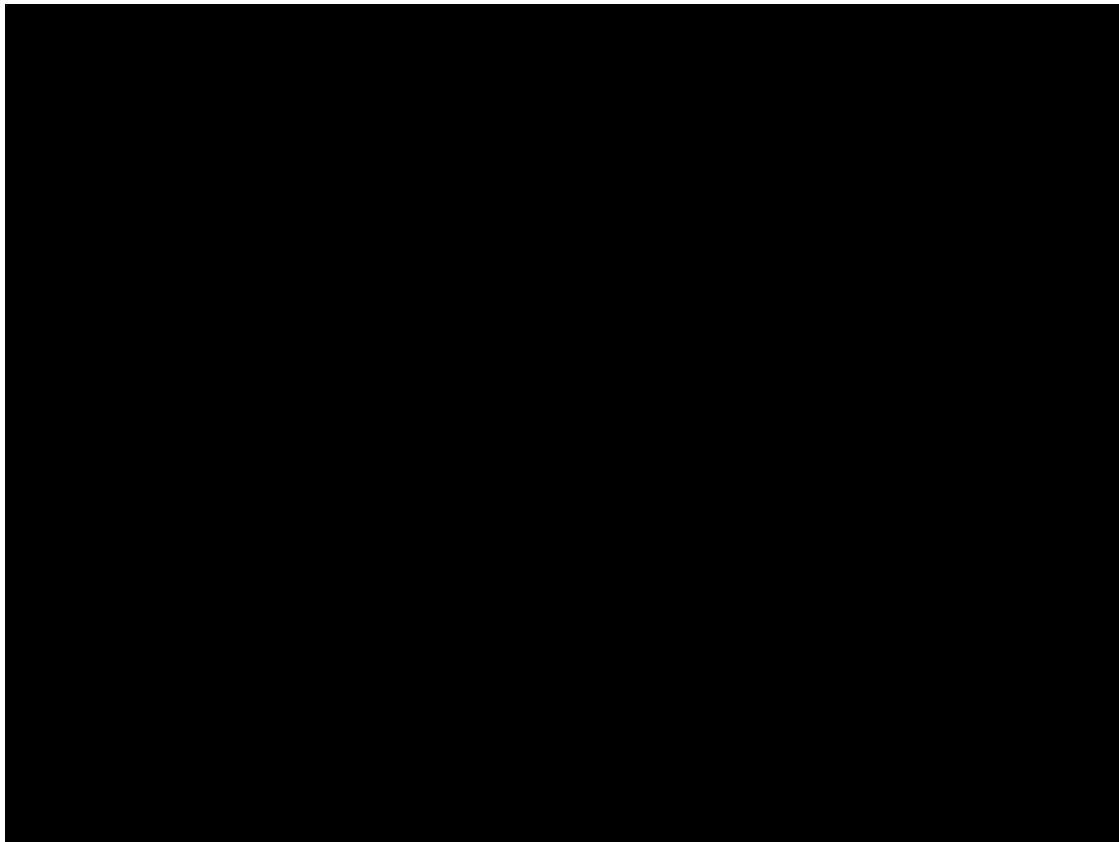
# Visual Odometry

- Feature Tracking/Extraction
  - Use any feature descriptor to extract features
- Depth Map Registration
  - Use a KD-tree to store the 3d points
  - Find 3 closest points
  - Form a planar patch
  - Project to the patch to get distance

# Motion Estimation

## Problem:

Compute camera motion  
between two consecutive  
frames using features with  
known and unknown depths



# Motion Estimation

Known  
distance

Unknown  
distance

$${}^S\mathbf{X}_i^k = \mathbf{R} {}^S\mathbf{X}_i^{k-1} + \mathbf{T}. \quad (1)$$

$${}^S\mathbf{X}_i^k = [{}^Sx_i^k, {}^Sy_i^k, {}^Sz_i^k]^T \quad {}^S\bar{\mathbf{X}}_i^k = [{}^S\bar{x}_i^k, {}^S\bar{y}_i^k, {}^S\bar{z}_i^k]^T$$

$$\|{}^S\bar{\mathbf{X}}_i^k\| = 1$$

$${}^S\mathbf{X}_i^k = {}^Sd_i^k {}^S\bar{\mathbf{X}}_i^k$$

Eliminate the  
distance term

$$({}^Sd_i^k) {}^S\bar{\mathbf{X}}_i^k = \mathbf{R} {}^S\mathbf{X}_i^{k-1} + \mathbf{T}$$

# Motion Estimation

$$\begin{array}{c}
 \text{Unknown distance} \rightarrow \\
 \text{Known distance} \rightarrow
 \end{array}
 \begin{array}{l}
 {}^S \mathbf{X}_i^k = \mathbf{R} {}^S \mathbf{X}_i^{k-1} + \mathbf{T}. \\
 {}^S d_i^k {}^S \bar{\mathbf{X}}_i^k = \mathbf{R} {}^S \mathbf{X}_i^{k-1} + \mathbf{T}
 \end{array}
 \quad (1)$$

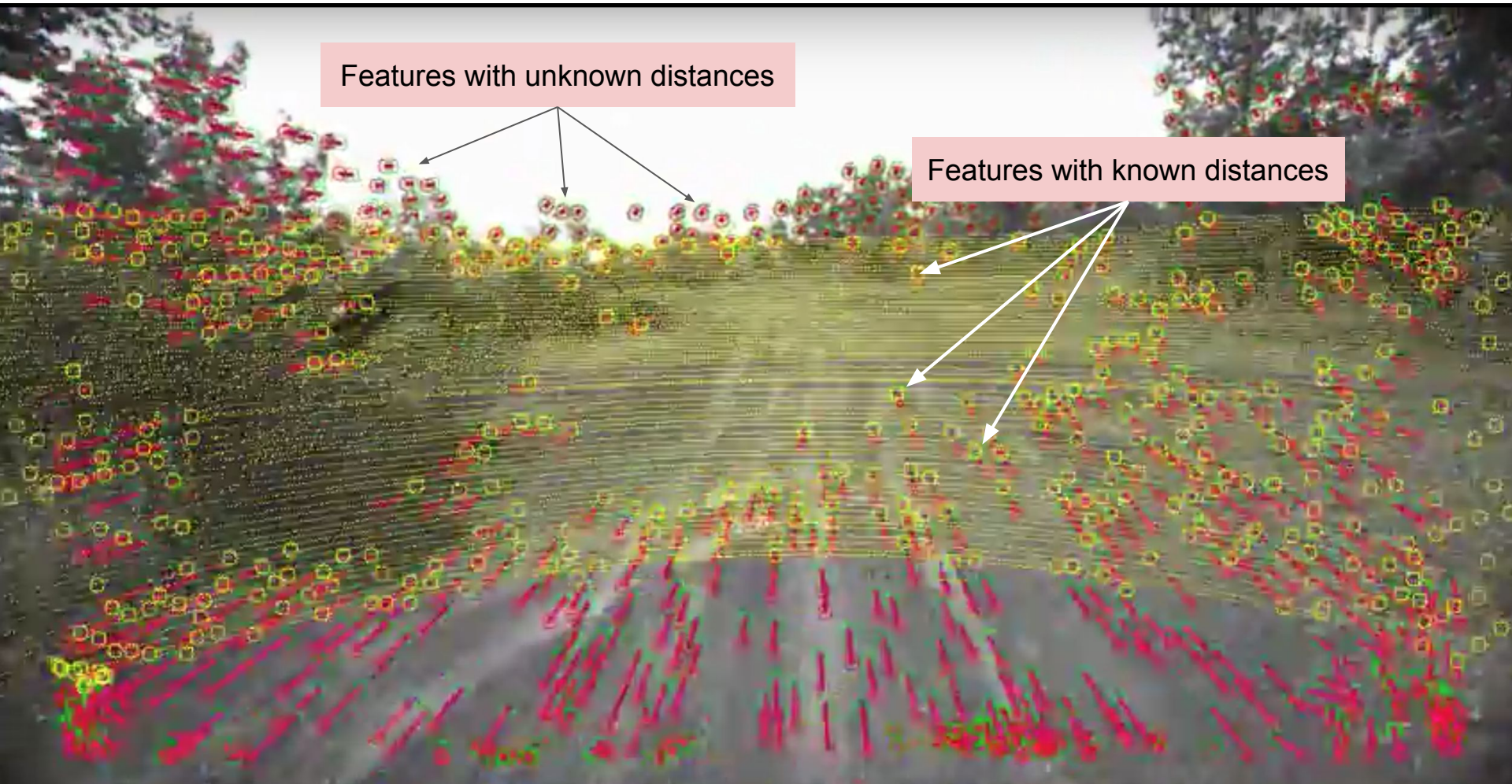
Combining first and second row with third row,

$$({}^S \bar{z}_i^k \mathbf{R}_1 - {}^S \bar{x}_i^k \mathbf{R}_3) {}^S \mathbf{X}_i^{k-1} + {}^S \bar{z}_i^k T_1 - {}^S \bar{x}_i^k T_3 = 0, \quad (2)$$

$$({}^S \bar{z}_i^k \mathbf{R}_2 - {}^S \bar{y}_i^k \mathbf{R}_3) {}^S \mathbf{X}_i^{k-1} + {}^S \bar{z}_i^k T_2 - {}^S \bar{y}_i^k T_3 = 0. \quad (3)$$

Features with unknown distances

Features with known distances



# Motion Estimation

$${}^S\mathbf{X}_i^{k-1} = S_{d_i^{k-1}} {}^S\bar{\mathbf{X}}_i^{k-1}$$

$${}^S\mathbf{X}_i^k = S_{d_i^k} {}^S\bar{\mathbf{X}}_i^k$$

Eliminate the  
distance terms

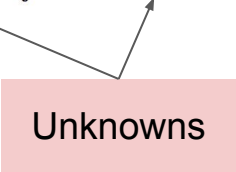
$$\begin{bmatrix} -S\bar{y}_i^k T_3 + S\bar{z}_i^k T_2 \\ S\bar{x}_i^k T_3 - S\bar{z}_i^k T_1 \\ -S\bar{x}_i^k T_2 + S\bar{y}_i^k T_1 \end{bmatrix} \mathbf{R} {}^S\bar{\mathbf{X}}_i^{k-1} = 0. \quad (4)$$

# Optimization

- Known distances - 2 equations
- Unknown distances - 1 equation

$${}^S\mathbf{X}_i^k = \mathbf{R} {}^S\mathbf{X}_i^{k-1} + \mathbf{T}.$$

Unknowns



$$\theta = [\theta_x, \theta_y, \theta_z]^T \quad \mathbf{R} = e^{\hat{\theta}} = \mathbf{I} + \frac{\hat{\theta}}{\|\theta\|} \sin \|\theta\| + \frac{\hat{\theta}^2}{\|\theta\|^2} (1 - \cos \|\theta\|),$$

$$f([\mathbf{T}; \theta]) = \epsilon, \quad \mathbf{J} = \partial f / \partial [\mathbf{T}; \theta].$$

$$[\mathbf{T}; \theta]^T \leftarrow [\mathbf{T}; \theta]^T - (\mathbf{J}^T \mathbf{J} + \lambda \text{diag}(\mathbf{J}^T \mathbf{J}))^{-1} \mathbf{J}^T \epsilon.$$



# Visual Odometry

$$(\mathbf{R}_1 - \bar{x}_i^k \mathbf{R}_3) \mathbf{X}_i^{k-1} + T_1 - \bar{x}_i^k T_3 = 0, \quad (3)$$

$$(\mathbf{R}_2 - \bar{y}_i^k \mathbf{R}_3) \mathbf{X}_i^{k-1} + T_2 - \bar{y}_i^k T_3 = 0, \quad (4)$$

$$[-\bar{y}_i^k T_3 + T_2, \bar{x}_i^k T_3 - T_1, -\bar{x}_i^k T_2 + \bar{y}_i^k T_1] \mathbf{R} \bar{\mathbf{X}}_i^{k-1} = 0. \quad (6)$$

$$\mathbf{R} = e^{\hat{\theta}} = \mathbf{I} + \frac{\hat{\theta}}{\|\theta\|} \sin \|\theta\| + \frac{\hat{\theta}^2}{\|\theta\|^2} (1 - \cos \|\theta\|), \quad (7)$$

$$f([\mathbf{T}; \theta]) = \epsilon, \quad (8)$$

$$[\mathbf{T}; \theta]^T \leftarrow [\mathbf{T}; \theta]^T - (\mathbf{J}^T \mathbf{J} + \lambda \text{diag}(\mathbf{J}^T \mathbf{J}))^{-1} \mathbf{J}^T \epsilon. \quad (9)$$

---

## Algorithm 1: Frame to Frame Motion Estimation

---

```

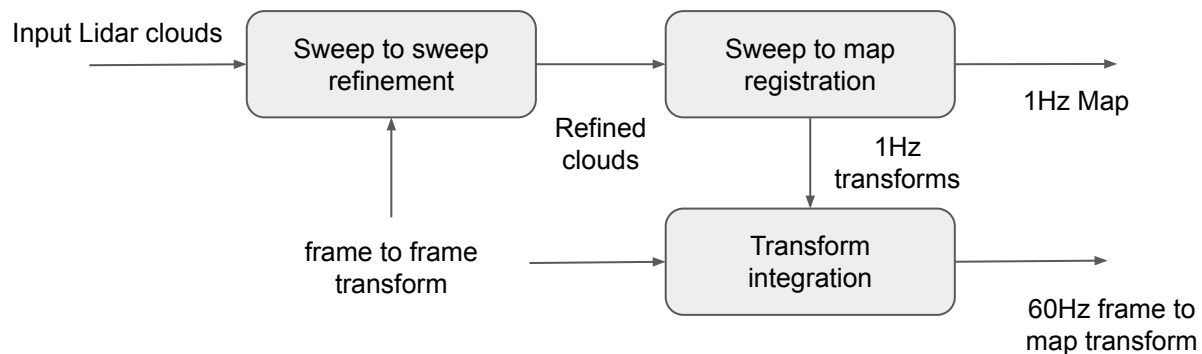
1  input :  $\bar{\mathbf{X}}_i^k, \mathbf{X}_i^{k-1}$  or  $\bar{\mathbf{X}}_i^{k-1}, i \in \mathcal{I}$ 
2  output :  $\theta, \mathbf{T}$ 
3  begin
4       $\theta, \mathbf{T} \leftarrow \mathbf{0}$ ;
5      for a number of iterations do
6          for each  $i \in \mathcal{I}$  do
7              if  $i$  is depth associated then
8                  Derive (3)-(4) using  $\bar{\mathbf{X}}_i^k$  and  $\mathbf{X}_i^{k-1}$ , substitute
                        (7) into (3)-(4) to obtain two equations, stack
                        the equations into (8);
9                  end
10                 else
11                     Derive (6) using  $\bar{\mathbf{X}}_i^k$  and  $\bar{\mathbf{X}}_i^{k-1}$ , substitute (7)
                                into (6) to obtain one equation, stack the
                                equation into (8);
12                     end
13                     Compute a bisquare weight for each feature
                                based on the residuals in (3)-(4) or (6);
14                     Update  $\theta, \mathbf{T}$  for one iteration based on (9);
15                 end
16                 if the nonlinear optimization converges then
17                     Break;
18                 end
19             end
20             Return  $\theta, \mathbf{T}$ ;
21 end

```

---



# Lidar Odometry



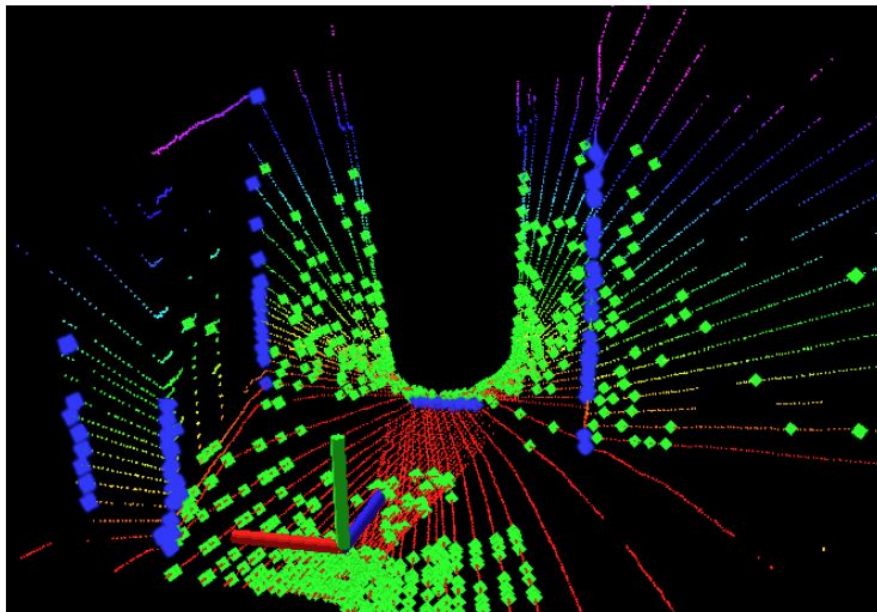
# Lidar Odometry

Smoothness term  
(or curvature)

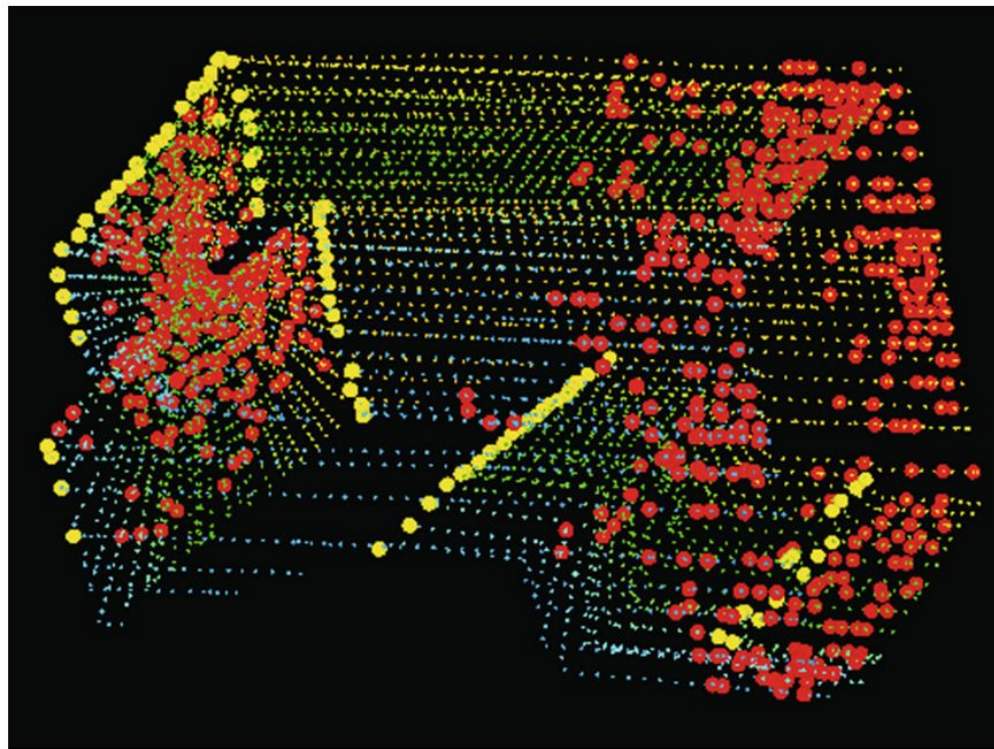
$$c = \frac{1}{|\mathcal{S}| \cdot \| \mathbf{X}_{(k,i)}^L \|} \left\| \sum_{j \in \mathcal{S}, j \neq i} (\mathbf{X}_{(k,i)}^L - \mathbf{X}_{(k,j)}^L) \right\|.$$

$\mathcal{S}$  contains half of its points on each side of  $i$  and 0.25 deg intervals between two points

# Lidar Odometry



Edge (blue) and planar (green) points



Edge (yellow) and planar (red) points

# Lidar Odometry

Smoothness term  
(or curvature)

$$c = \frac{1}{|\mathcal{S}| \cdot \|X_{(k,i)}^L\|} \left\| \sum_{j \in \mathcal{S}, j \neq i} (X_{(k,i)}^L - X_{(k,j)}^L) \right\|.$$

$\mathcal{S}$  contains half of its points on each side of  $i$  and 0.25 deg intervals between two points

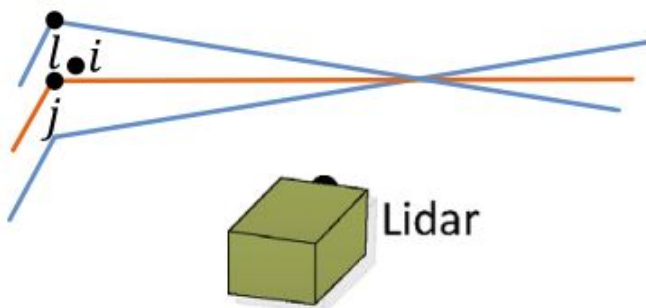
## Edge points

- Find two closest point in edge set
- Construct a line
- Find point to line distance

## Planar points

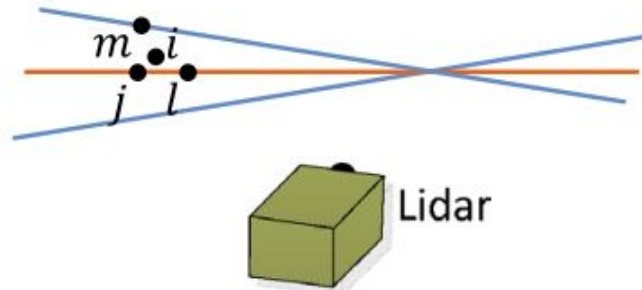
- Find three closest point in planar set
- Construct a patch
- Find point to plane distance

# Lidar Odometry



## Edge points

- Find two closest point in edge set
- Construct a line
- Find point to line distance

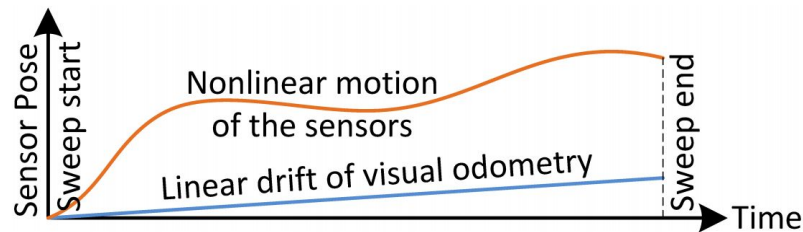


## Planar points

- Find three closest point in planar set
- Construct a patch
- Find point to plane distance

# Sweep to Sweep Refinement

- Removes point cloud distortion
- Models as linear drift



$$\mathbf{T}'_i = \mathbf{T}' (t_i - t^m) / (t^{m+1} - t^m).$$

6x1 vector describing the linear drift

Time between the start of sweep to the current point

Total time between current and previous sweeps

# Sweep to Sweep Refinement

$$\mathbf{T}'_i = \mathbf{T}' \underbrace{(t_i - t^m)}_{\text{Time between the start of sweep to the current point}} / \underbrace{(t^{m+1} - t^m)}_{\text{Total time between current and previous sweeps}}.$$

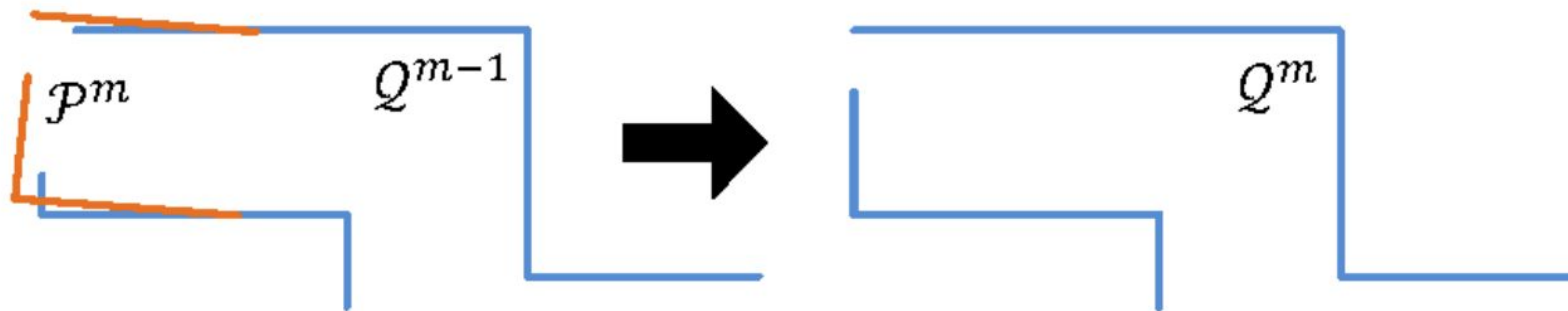
6x1 vector describing the  
linear drift

Time between the start of  
sweep to the current point

Total time between current  
and previous sweeps

$$f({}^S\mathbf{X}_i^m, \mathbf{T}'_i) = d_i,$$

# Sweep to Map Registration





# Transform Integration

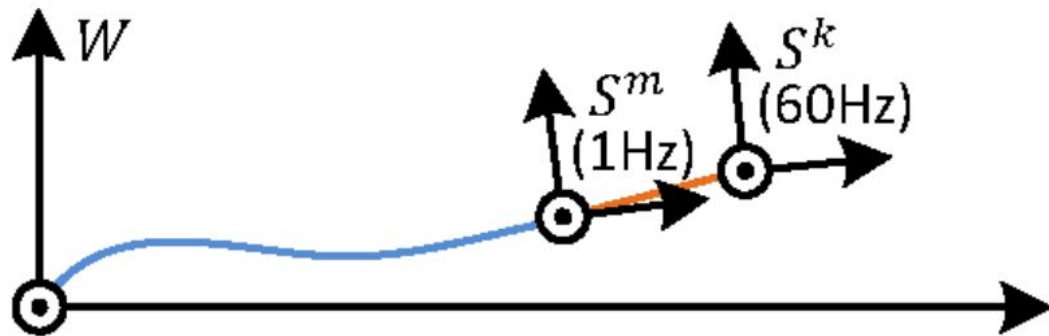


Fig. 7. Illustration of transform integration. The blue segment represents transforms published by the lidar odometry at a low frequency, regarding sensor poses in the world coordinate system  $\{W\}$ . The orange segment represents transforms published by the visual odometry at a high frequency containing frame to frame motion. The two transforms are integrated to generate high frequency sensor pose outputs at the image frame rate.

# Experiments and Results

## Datasets

- KITTI
- Custom

## Tests

- Accuracy
- Robustness

# Accuracy Tests

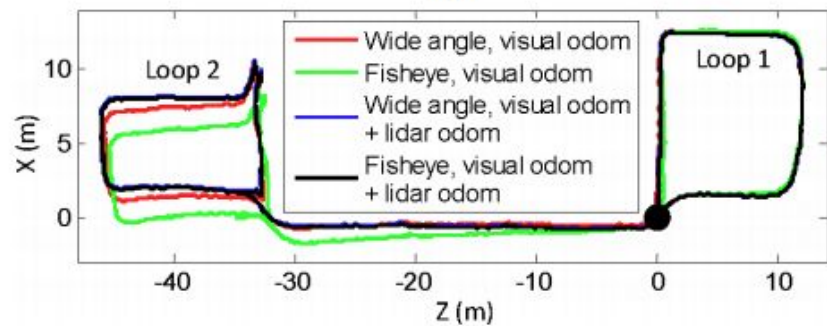
## RELATIVE POSITION ERRORS IN ACCURACY TESTS

W: WIDE-ANGLE, F: FISHEYE, V: VISUAL ODOM (1ST SECTION IN FIG. 2), VL: VISUAL ODOM + LIDAR ODOM (BOTH SECTIONS IN FIG. 2).

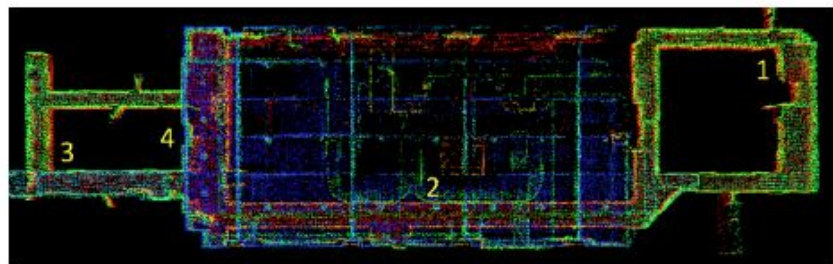
Test No.	Dist.	Relative Position Error			
		W-V	F-V	W-VL	F-VL
Test 1 (Loop 1)	49m	<b>1.1%</b>	1.8%	<b>0.31%</b>	<b>0.31%</b>
Test 1 (Loop 2)	47m	<b>1.0%</b>	2.1%	<b>0.37%</b>	<b>0.37%</b>
Test 2	186m	<b>1.3%</b>	2.7%	<b>0.63%</b>	0.64%
Test 3	538m	<b>1.4%</b>	3.1%	<b>0.71%</b>	0.73%



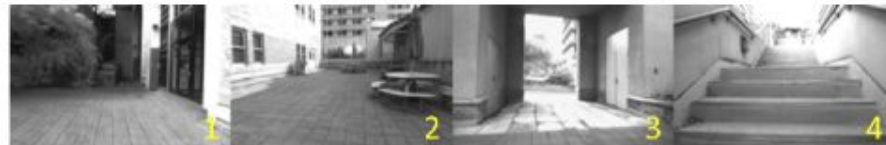
(a)



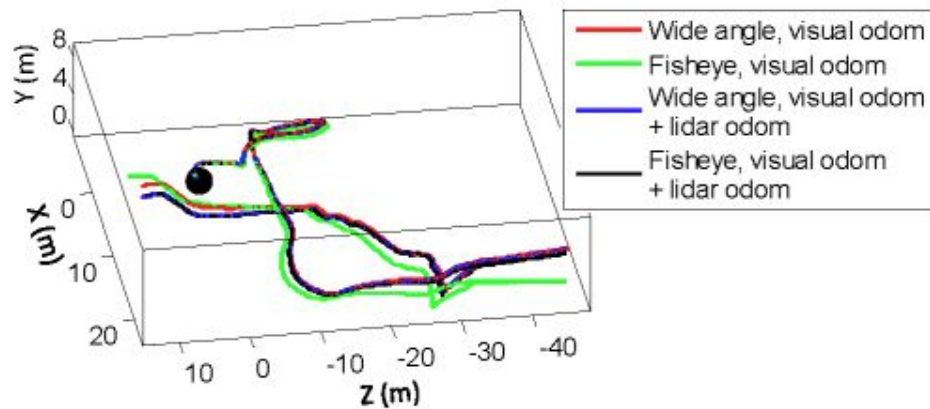
(b)



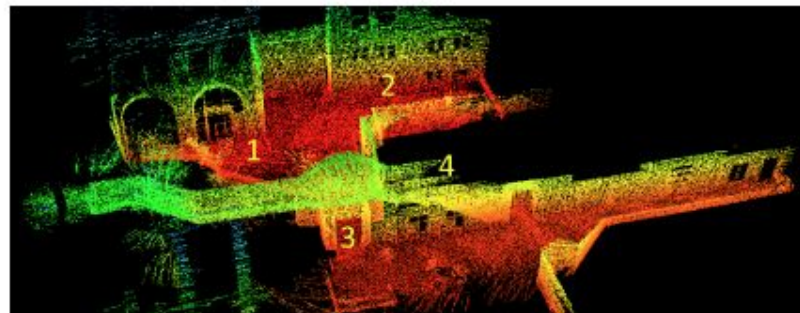
(c)



(a)



(b)



(c)

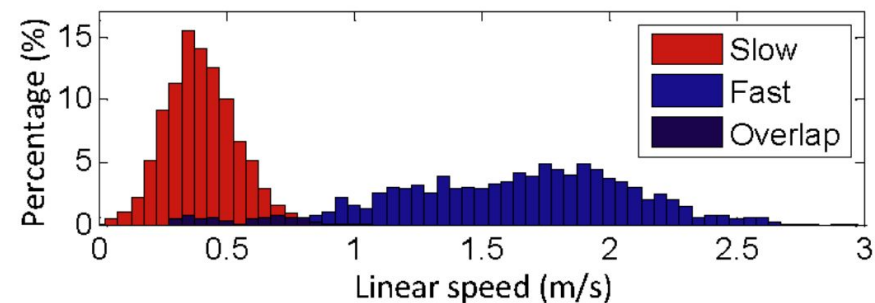
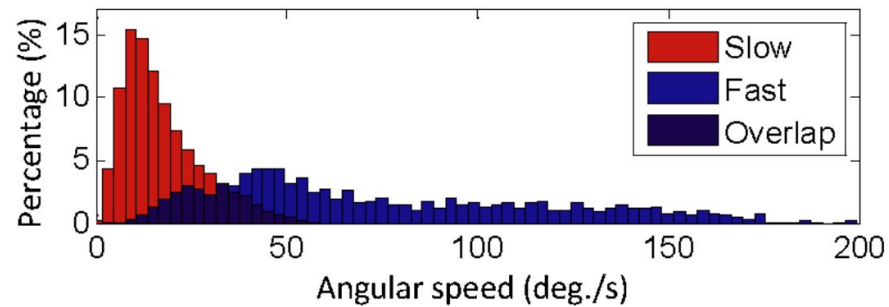
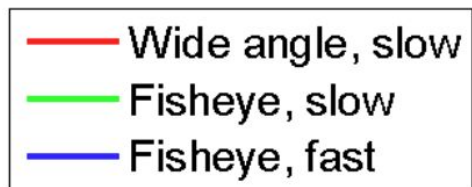
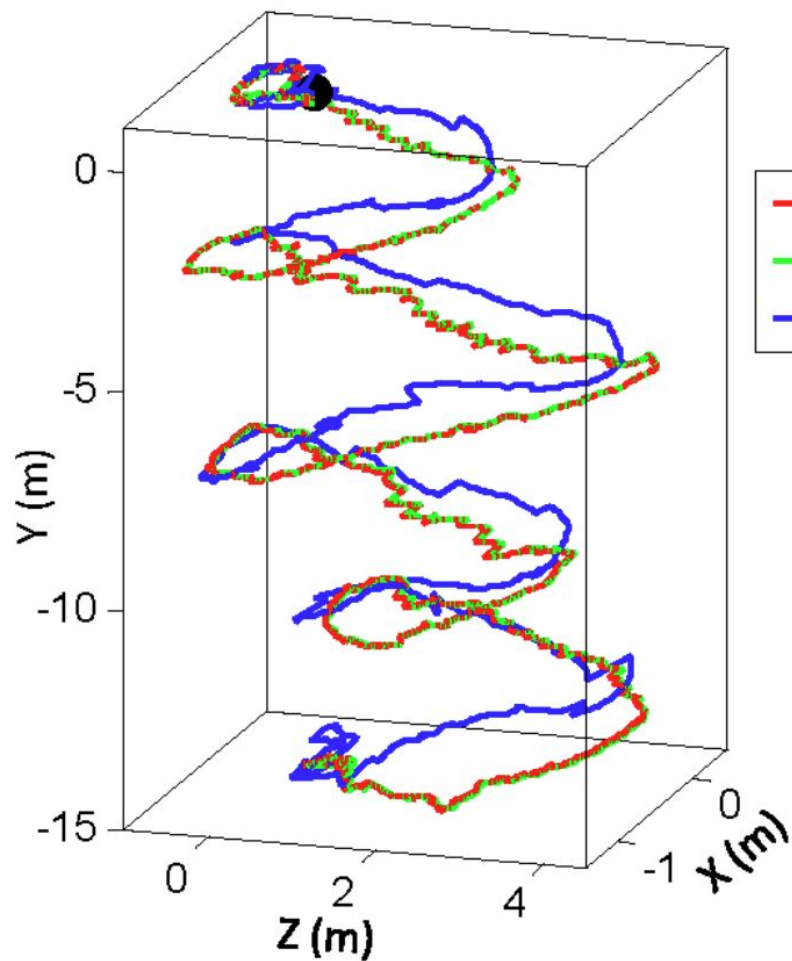
# Robustness Tests

## RELATIVE POSITION ERRORS IN FAST MOTION TESTS

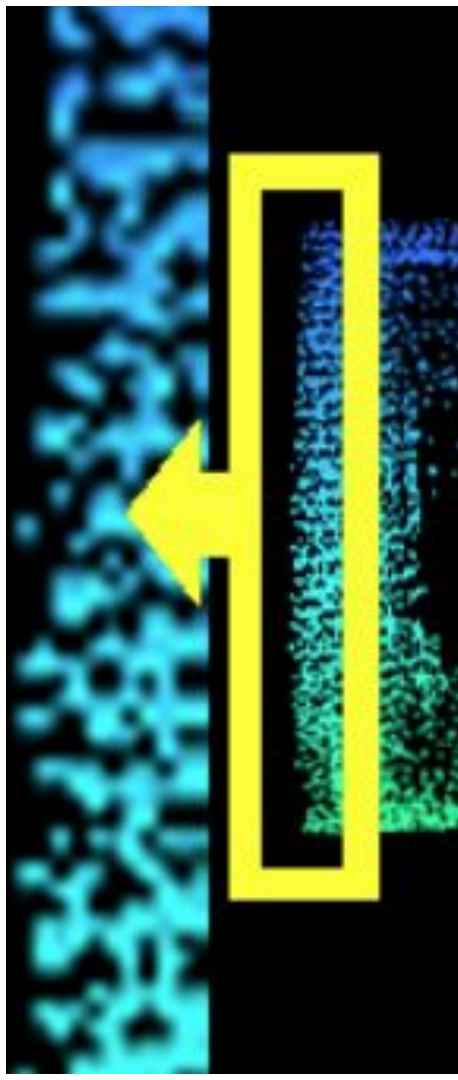
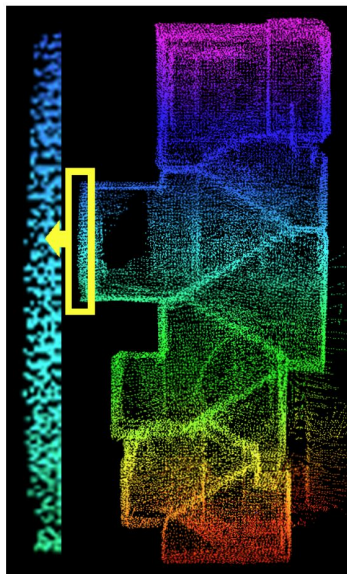
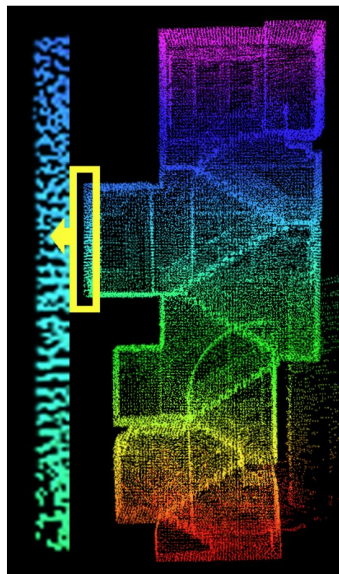
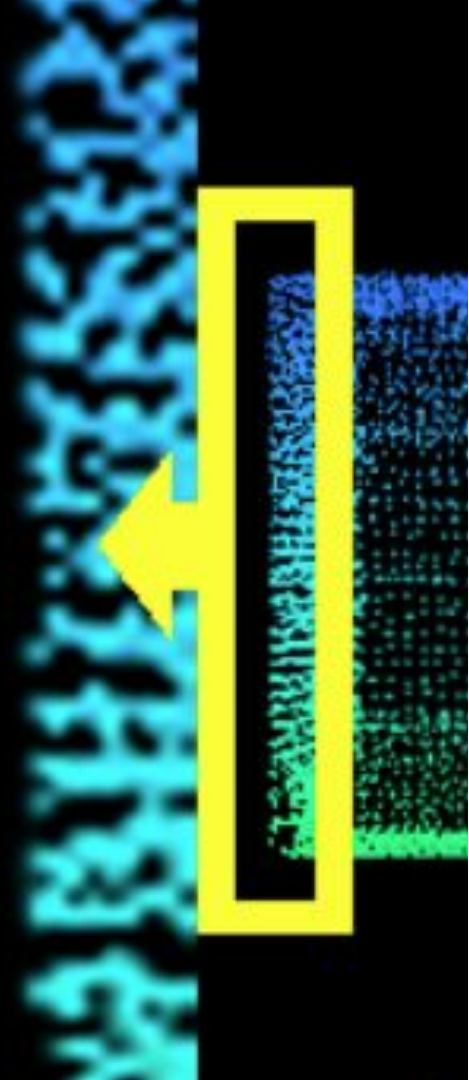
W: WIDE-ANGLE, Fi: FISHEYE, S: SLOW, Fa: FAST.

Test No.	Dist.	Relative Position Error			
		W-S	Fi-S	W-Fa	Fi-Fa
Test 4	66m	<b>0.67%</b>	0.68%	Failed	<b>1.3%</b>
Test 5	54m	<b>0.27%</b>	0.28%	Failed	<b>0.39%</b>





(a)



Questions?