

SLAM STATE ESTIMATION IN DEGENERATE SCENES

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STATE ESTIMATION IN SLAM

- In SLAM methods, we usually use frame by frame comparison to estimate sensor pose transform or state vector
- This is commonly done by comparing and matching texture feature (visual) or geometric feature (point cloud) between frames
- To estimate state vector, we minimize a cost function that comes from observation and puts constraints on state vector
- The cost function can be linearized

$$\arg \min_x f^2(x)$$

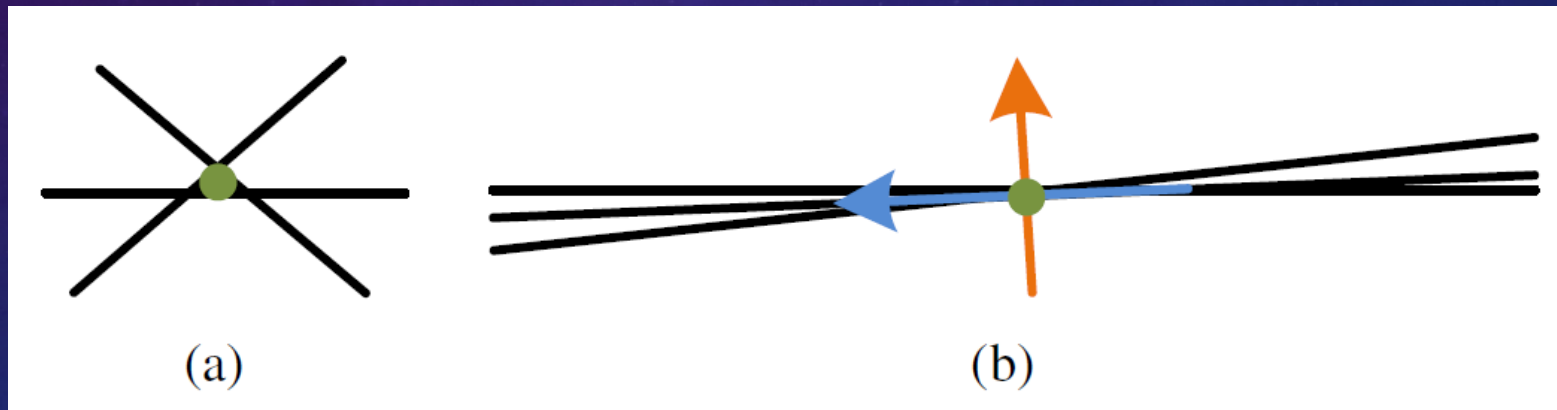
$$\mathbf{J} = \partial f(x) / \partial x$$

$$\arg \min_x \|\mathbf{A}x - \mathbf{b}\|^2$$



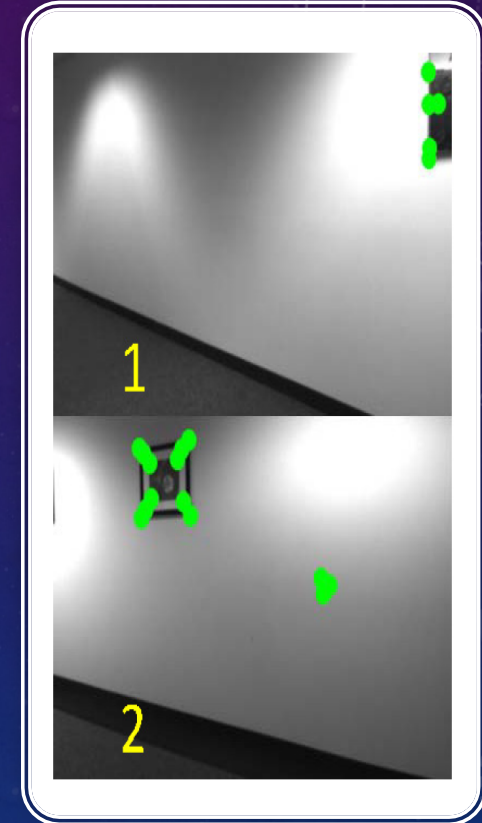
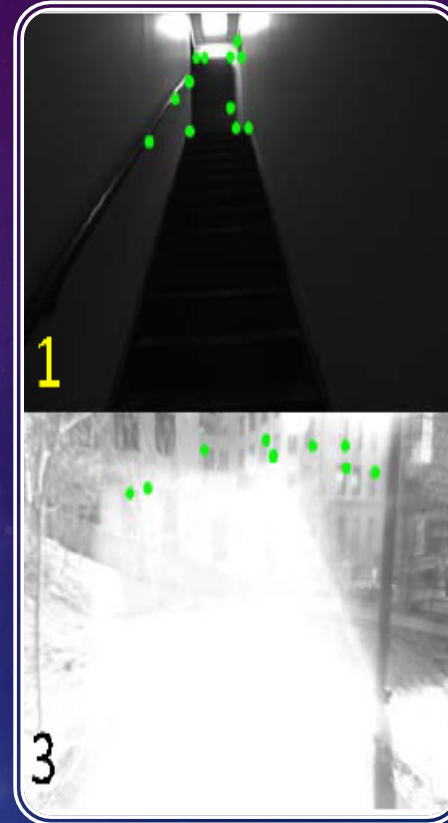
DEGENERACY

- Degeneracy occurs when constraints are ill-conditioned in some directions of state vector space
- We attempt to detect and separate these directions
- We only solve the problem in well-conditioned directions



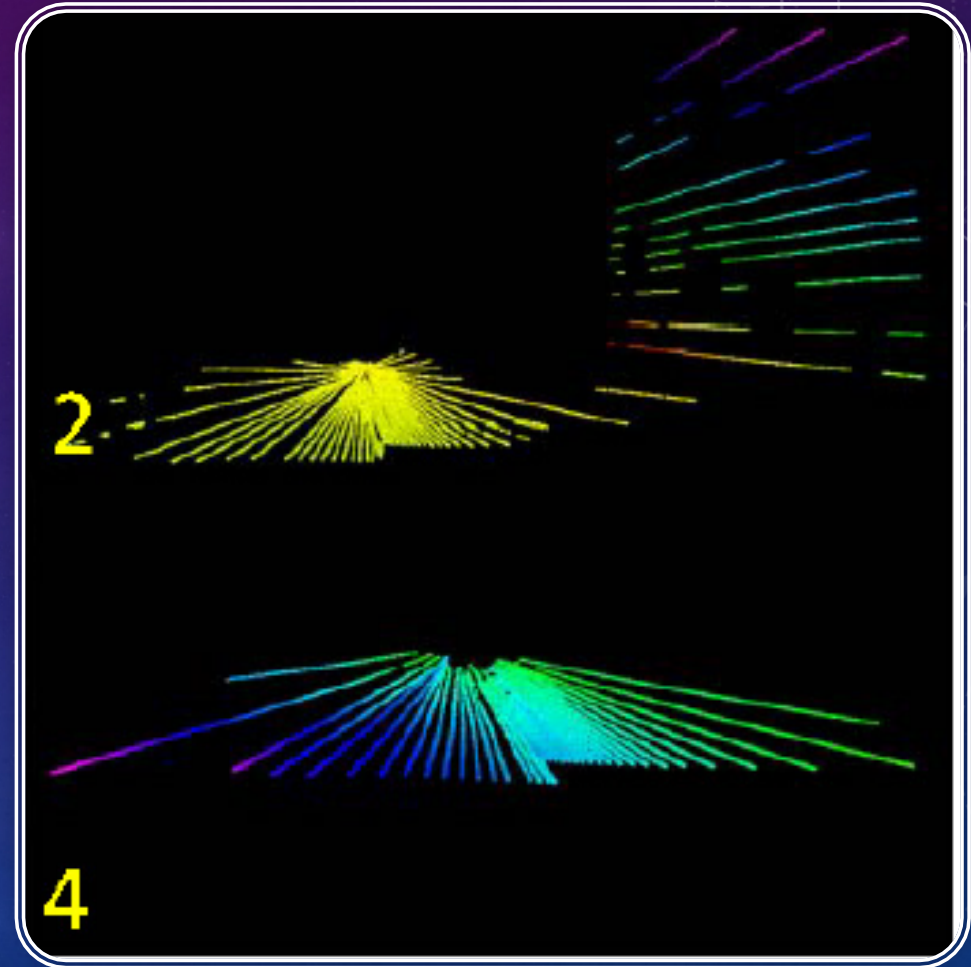
DEGENERATE SCENE - VISUAL

- Visual degeneracy occurs when there are not enough texture features
- Examples: large area of white wall, camera pointing to the sun, dark environment



DEGENERATE SCENE - POINT CLOUD

- Point cloud (LiDAR) degenerate scene occurs when there are not enough geometric features
- Example: large area of ground, plane or other planar object



DEGENERACY DIRECTION

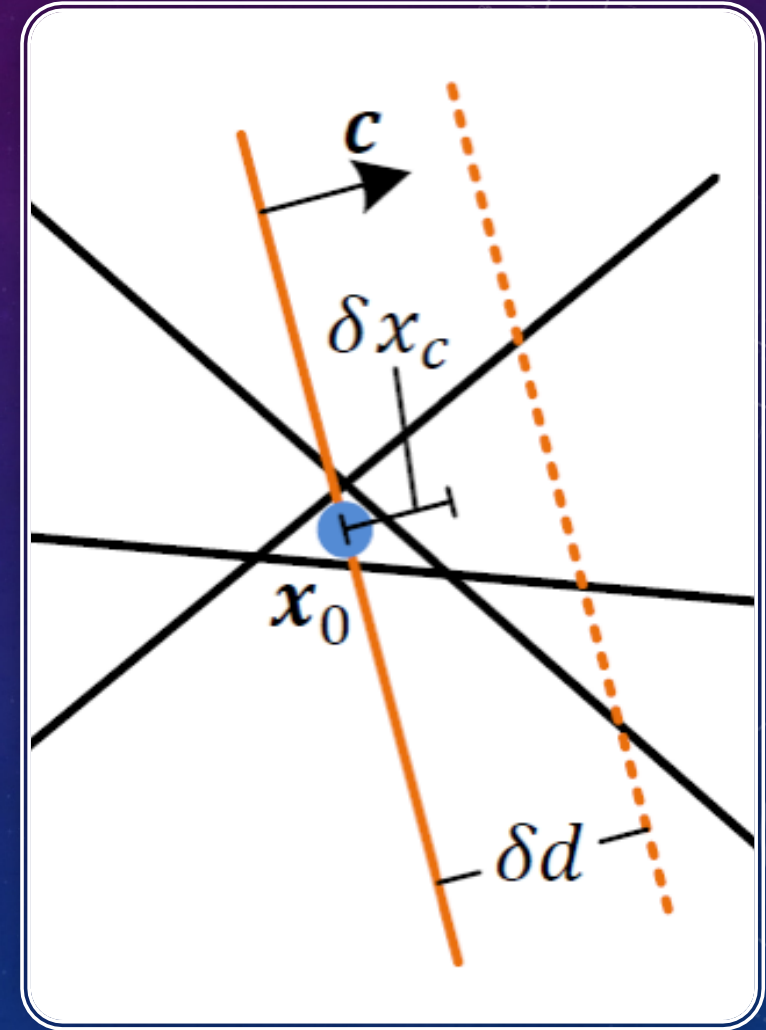
- Measures how sensitive the solution is to a small perturbation

- Additional constraint

$$\mathbf{c}^T (\mathbf{x} - \mathbf{x}_0) = 0, \quad \|\mathbf{c}\| = 1$$

- Make perturbation δd along \mathbf{c}
- Find maximum shift direction

$$\delta x_c^* = \max_{\mathbf{c}} \delta x_c$$



DEGENERACY FACTOR

- Maximum shift δx_c^* gives the least stable direction of the solution, which is the direction degeneracy is defined
- Degeneracy factor is the ratio of perturbation to maximum solution shift

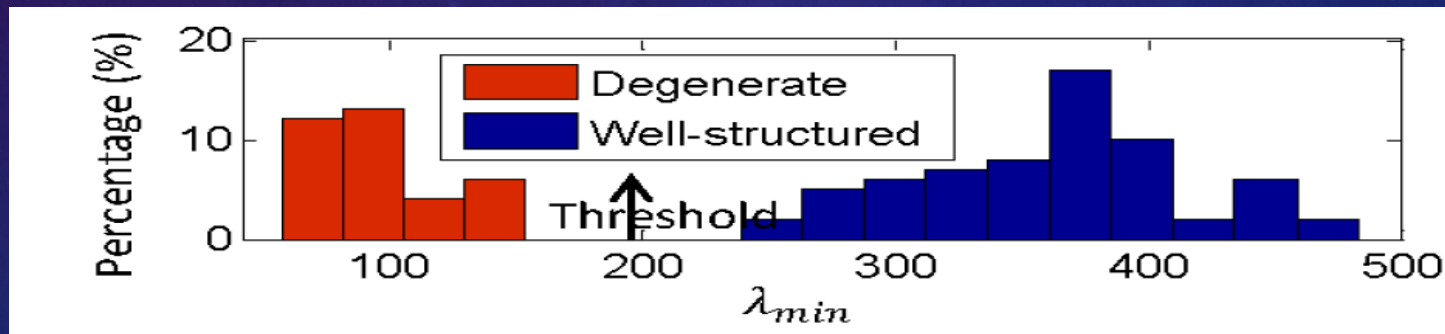
$$\mathcal{D} = \delta d / \delta x_c^*$$

- Greater degeneracy factor means more stable solution
- For linearized problem $\arg \min_x \|\mathbf{A}\mathbf{x} - \mathbf{b}\|^2$, degeneracy factor D only depends on A , but not b
- For linearized problem $\arg \min_x \|\mathbf{A}\mathbf{x} - \mathbf{b}\|^2$, degeneracy factor $D = \lambda_{min} + 1$, where λ_{min} is the smallest eigenvalue of $A^T A$



EIGENVALUE AND EIGENVECTOR

- In linearized problem $\arg \min_x \|\mathbf{Ax} - \mathbf{b}\|^2$, we can assume matrix A is non singular, thus $A^T A$ is positive definite
- Eigenvalues of $A^T A$ are listed, in increasing order, as $\lambda_1, \dots, \lambda_n$ and the corresponding eigenvectors are v_1, \dots, v_n
- Each eigenvalue corresponds to one direction (dimension) in state space
- Find certain threshold to determine which dimensions are degenerate



SOLUTION REMAPPING

- Suppose the smallest m eigenvalues are determined to be degenerate, construct three matrices, which represent degenerate, non-degenerate, whole space respectively

$$\begin{aligned}\mathbf{V}_p &= [\mathbf{v}_1, \dots, \mathbf{v}_m, 0, \dots, 0]^T, \\ \mathbf{V}_u &= [0, \dots, 0, \mathbf{v}_{m+1}, \dots, \mathbf{v}_n]^T, \\ \mathbf{V}_f &= [\mathbf{v}_1, \dots, \mathbf{v}_m, \mathbf{v}_{m+1}, \dots, \mathbf{v}_n]^T\end{aligned}$$

- x_p is the best guess for true state and x_u is the unaltered solution
- x_p is given by some a priori model, such as constant velocity model
- The final solution is $\mathbf{x}_f = \mathbf{x}'_p + \mathbf{x}'_u$, where $\mathbf{x}'_p = \mathbf{V}_f^{-1} \mathbf{V}_p \mathbf{x}_p$ and $\mathbf{x}'_u = \mathbf{V}_f^{-1} \mathbf{V}_u \mathbf{x}_u$

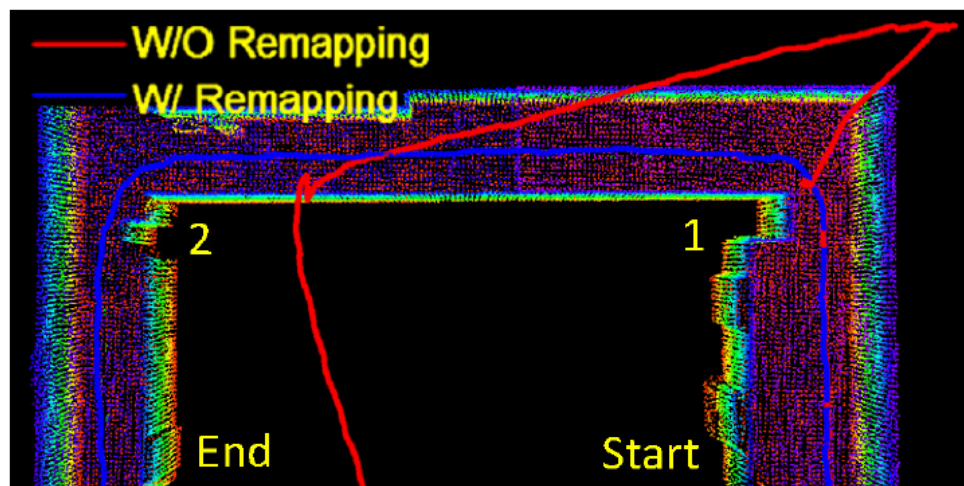


Algorithm 1: Nonlinear Solver with Solution Remapping

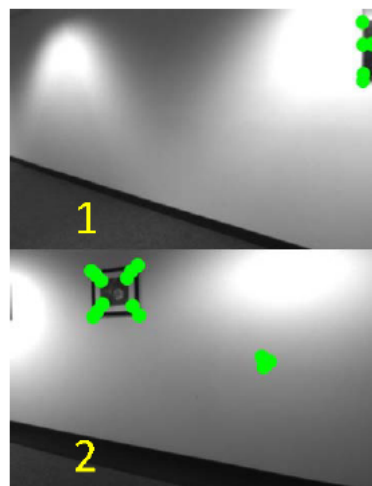
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1 input :  $f$  (nonlinear function),  $\mathbf{x}_p$  (predicted solution)
2 output :  $\mathbf{x}_f$  (final solution)
3 begin
4    $\mathbf{x}_f \leftarrow \mathbf{x}_p$ ;  $O(*)$ 
5   Linearize  $f$  at  $\mathbf{x}_p$  to get  $\mathbf{A}$ ,  $\mathbf{b}$ , and  $\mathbf{A}^T \mathbf{A}$ ;  $O(*)$ 
6   Compute  $\lambda_i$  and  $\mathbf{v}_i$  of  $\mathbf{A}^T \mathbf{A}$ ,  $i = 1, \dots, n$ ;  $O(n^3)$ 
7   Determine a number  $m$  of  $\lambda_i$  smaller than a threshold,
   construct  $\mathbf{V}_p$ ,  $\mathbf{V}_u$ , and  $\mathbf{V}_f$  based on (15)-(17);  $O(n^2)$ 
8   while nonlinear iterations do  $O(kn^2 + *)$ 
9     Compute update  $\Delta \mathbf{x}_u$ ;  $O(*)$ 
10     $\mathbf{x}_f \leftarrow \mathbf{x}_f + \mathbf{V}_f^{-1} \mathbf{V}_p \Delta \mathbf{x}_u$ ;  $O(n^2)$ 
11  end
12  Return  $\mathbf{x}_f$ ;
13 end
```

ALGORITHM

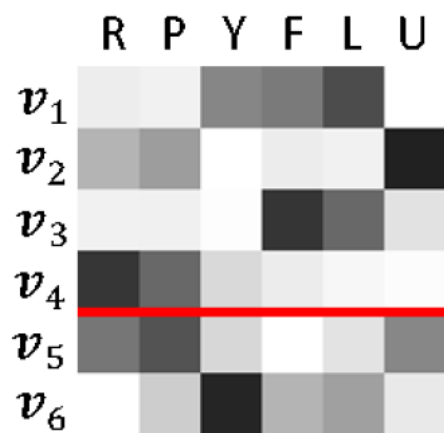
- Local linearization for non linear system
- Degenerate directions only calculated once
- This algorithm adds $O(kn^2 + n^3)$ in time complexity, where k is iteration steps and n is dimension of state space



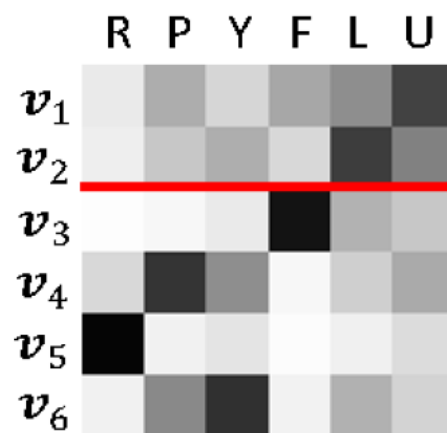
(a) Map



(b) Image features



(c) Location 1



(d) Location 2

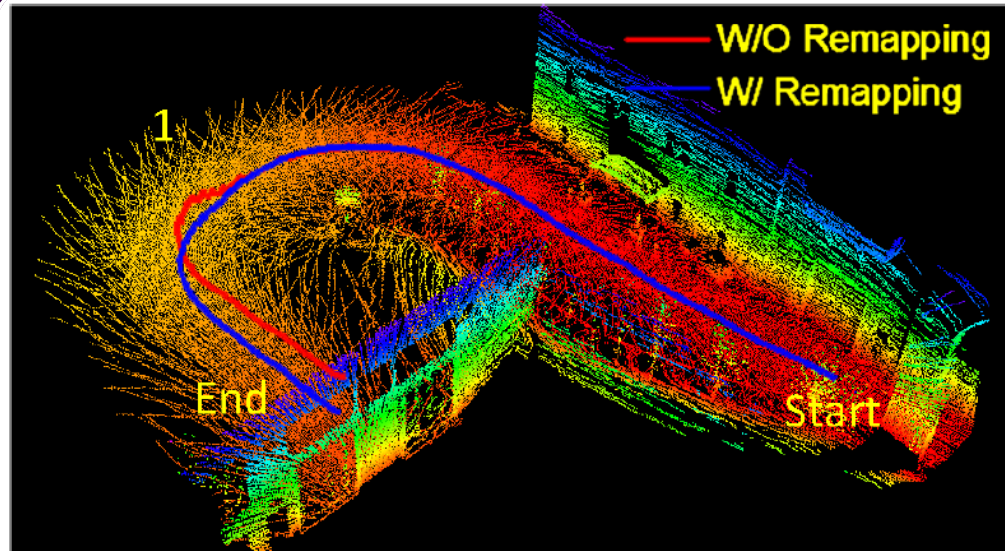
R: roll
P: pitch
Y: yaw
F: forward
L: left
U: up

(e)

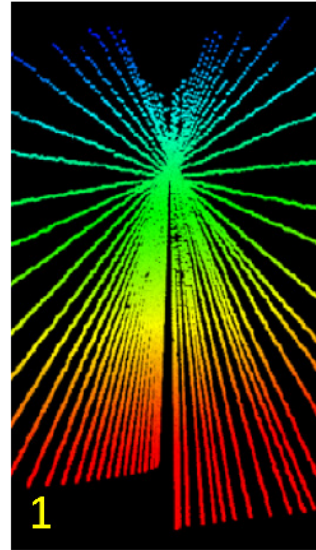
EXPERIMENT - VISUAL

- Two feature-poor scenes 1 and 2, with four and two degenerate directions respectively
- Huge error at 1 and small error at 2 without remapping
- Constant velocity model

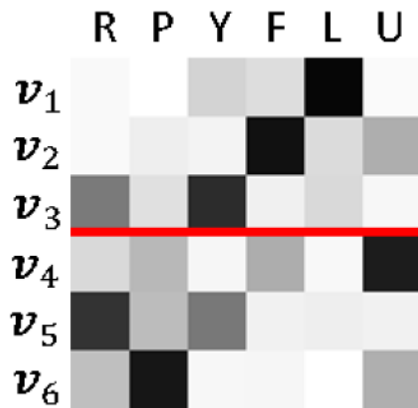
EXPERIMENT - POINT CLOUD



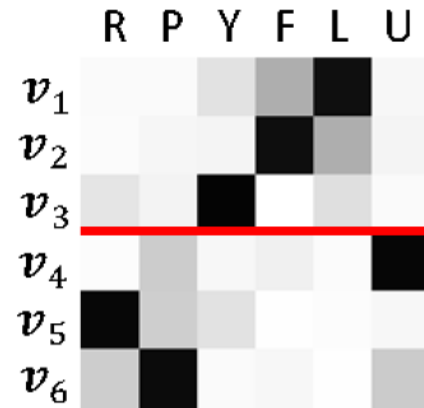
(a) Map



(b) Lidar scan



(c) Sweep to sweep

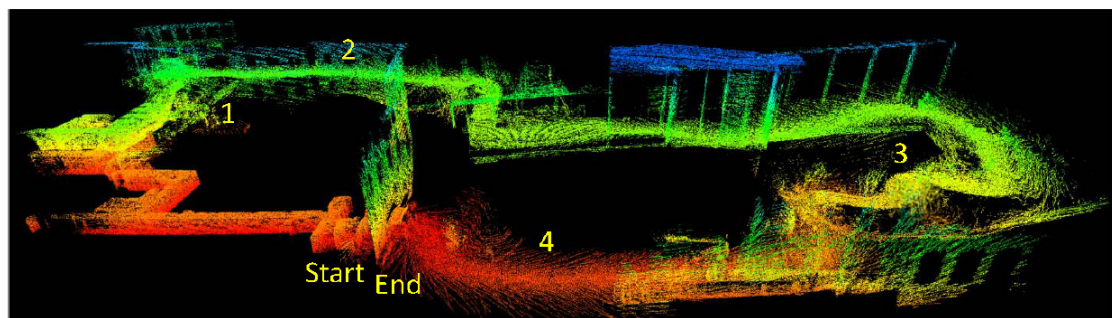


(d) Sweep to map

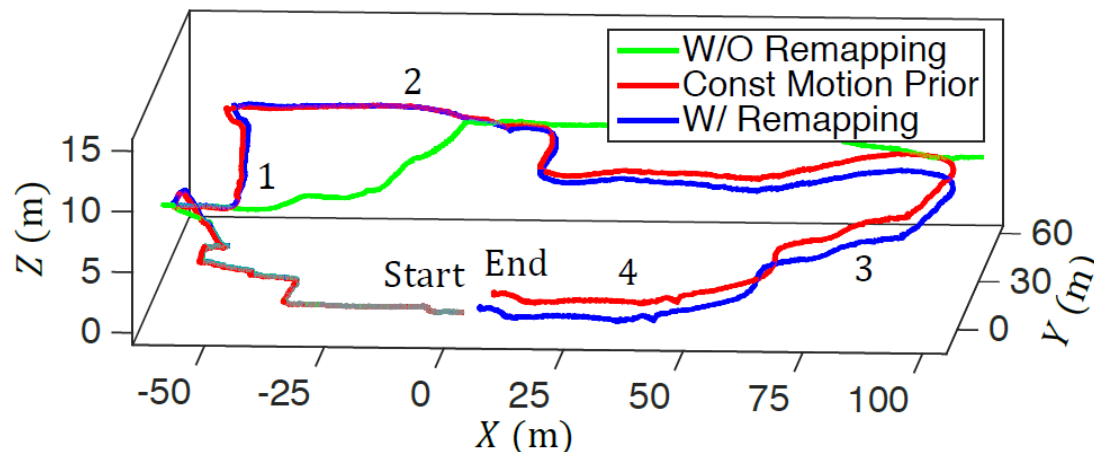
R: roll
P: pitch
Y: yaw
F: forward
L: left
U: up

(e)

- Planar scene at 1 (flat ground)
- Odometry error around scene 1
- Constant velocity model



(a) Map



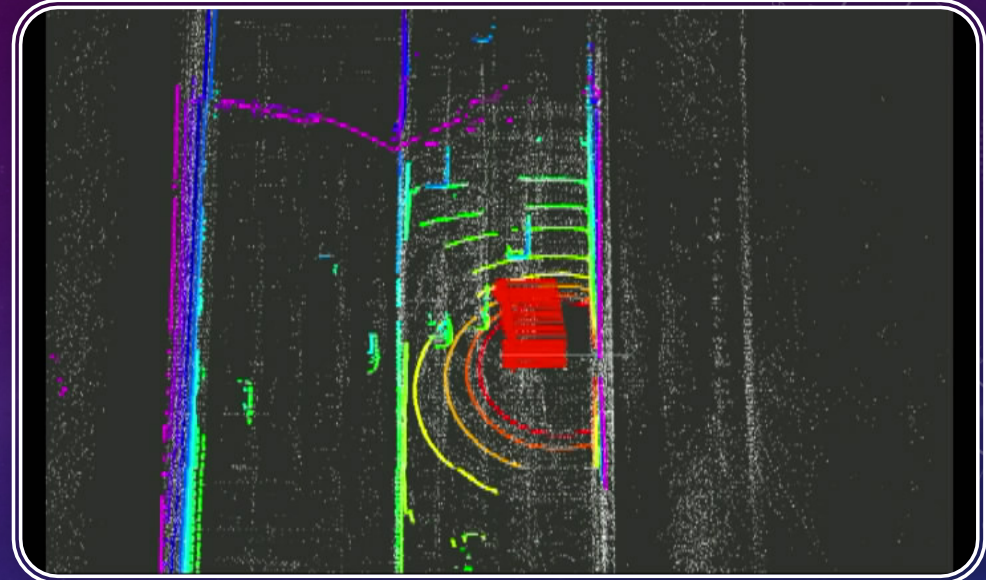
EXPERIMENT - VISUAL AND POINT CLOUD

- Visual degeneracy at 1 and 3 due to poor lighting
- Point cloud degeneracy at 2 and 4 due to flat ground/wall
- Total distance 538 meters and final relative position error 0.71% (3.8 meters)



OUR EXPERIENCE

- Our drive test in a tunnel with LiDAR point cloud
- Scene dominated by a flat wall on one side and moving vehicles (dynamic noise)
- LOAM produces stationary or slightly backwards odometry



OUR PLANNED TEST

- In LOAM algorithm, current frame pose is estimated by combining edge point planar point constraints $f(\mathbf{T}_k^L(t)) = d$
- The Jacobian is calculated as $\mathbf{J} = \partial f / \partial \mathbf{T}_k^L(t)$
- So we can calculate and order eigenvalues of $J^T J$ to detect degeneracy
- Actual threshold needs to be tested and determined depending on scene
- Dynamic noise (moving vehicles, cyclists, people) is still a concern



FINAL THOUGHTS

- Runs efficiently if dimension of state space is small (time complexity is $O(kn^2 + n^3)$)
- Threshold of eigenvalues need to be chosen based on experiments and thus depends on scenes
- Able to detect degeneracy, but correction is another story
- In degenerate directions, prediction (e.g. constant velocity model) is used to estimate state
- Other sensor, such as IMU or odometer, can provide more accurate prediction than constant velocity model
- Other than degeneracy, dynamic noise is another obstacle to SLAM



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