Learning for Active 3D Mapping

Karel Zimmermann, Tomáš Petříček, Vojtěch Šalanský, Tomáš Svoboda

http://cmp.felk.cvut.cz/~zimmerk/

ICCV 2017

Vision for Robotics and Autonomous Systems
https://cyber.felk.cvut.cz/vras/

Center for Machine Perception
https://cmp.felk.cvut.cz

Department for cybernetics
Faculty of Electrical Engineering
Czech Technical University in Prague

Czech Technical University in Prague
Faculty of Electrical Engineering, Department of Cybernetics
Motivation

- **Motivation:** New Solid State Lidars will allow independent steering of depth-measuring rays.

S3 principle

- Emitted laser beams
- Transmitted through Optical Phased Array
- Controlling optical properties of OPA elements, allows to steer laser beams in desired directions
- Reflected laser beams are captured by SPAD array
Problem definition

1. Learn to reconstruct dense 3D voxel map from sparse depth measurements
Problem definition

1. Learn to reconstruct dense 3D voxel map from sparse depth measurements
2. Optimize reactive control of depth-measuring rays along an expected vehicle trajectory

Images of S3 Lidar redistributed with permission of Quanergy Systems (http://quanergy.com)
Czech Technical University in Prague
Faculty of Electrical Engineering, Department of Cybernetics
Overview of active 3D mapping

- Learning of 3D mapping network \( M(x|\theta) \)
Overview of active 3D mapping

- Learning of 3D mapping network \( M(x|\theta) \)
- Planning of depth measuring rays \( J(\theta) \)
Overview of active 3D mapping

- Learning of 3D mapping network \( M(x|\theta) \)
- Planning of depth measuring rays \( J(\theta) \)
- SSL provides following sparse measurement \( x(\theta) \)

\[ y(x(\theta), \theta) \]
Learning & Planning minimize common objective

$$\arg\min_\theta \sum_{\text{voxels}} \mathcal{L}(\cdot)$$

$$\mathbf{x}(\theta)$$

$$M(\mathbf{x}|\theta)$$

$$\mathbf{y}(\mathbf{x}(\theta), \theta)$$

$$J(\theta)$$
Learning & Planning minimize common objective

$$\arg \min_{\theta} \sum_{\text{voxels}} \mathcal{L}(\cdot), \quad y^*$$

$x(\theta)$

$y(x(\theta), \theta)$

$\mathcal{L}(\cdot)$

$J(\theta)$

Czech Technical University in Prague
Faculty of Electrical Engineering, Department of Cybernetics
Learning & Planning minimize common objective

\[
\arg \min_{\theta} \sum_{\text{voxels}} \mathcal{L}(y(x(\theta), \theta), y^*) \text{ subject to } |J_\ell(\theta)| \leq K
\]
Learning as minimization over $\theta$

$$\operatorname{arg\ min}_\theta \sum_{\text{voxels}} L(y(x(\theta), \theta), y^*) \text{ subject to } |J_\ell(\theta)| \leq K$$

Result of planning is not differentiable

$x(\theta)$

$y(x(\theta), \theta)$
Locally approximate objective around $\theta^0$

$$\arg\min_\theta \sum_{\text{voxels}} \mathcal{L}(y(x(\theta^0), \theta), y^*) \quad \text{subject to } |J_\ell(\theta^0)| \leq K$$
Minimize approximated objective to get $\theta^1$

$$
\theta^1 = \arg\min_{\theta} \sum_{\text{voxels}} \mathcal{L}(y(x(\theta^0), \theta), y^*)
$$
Minimize approximated objective to get $\theta^1$

$$\arg \min_{\theta} \sum_{\text{voxels}} \mathcal{L}(y(x(\theta^1), \theta), y^*)$$
Minimize approximated objective to get $\theta^1$

$$
\theta^2 = \arg \min_{\theta} \sum_{\text{voxels}} \mathcal{L}(y(x(\theta^1), \theta), y^*)
$$
Iteratively optimize approximated objective

\[
\theta^{t+1} = \arg \min_{\theta} \sum_{\text{voxels}} \mathcal{L}(y(x(\theta^t), \theta), y^*)
\]

\[
\theta^0 \rightarrow \theta^1 \rightarrow \theta^2 \rightarrow \ldots \rightarrow \theta^t \rightarrow \theta^{t+1} \rightarrow \ldots
\]

• Fix point of this mapping would assure:
  • local optimality of the objective
  • statistical consistency of the learning

• In practise, we iterate until validation error stops decreasing
Planning of depth measuring rays $J$

- No ground truth $y^*$ available online
- Objective for planning is approximated
Planning of depth measuring rays \( J \)

- No ground truth \( y^* \) available online
- Objective for planning is approximated from current map
Planning of depth measuring rays $J$

- No ground truth $y^*$ available online
- Objective for planning is approximated from current map $y$

\[
\begin{align*}
\text{occupied} & \quad \text{unoccupied} \\
\sigma(y) & \quad 1 - \sigma(y)
\end{align*}
\]
Planning of depth measuring rays $J$

- No ground truth $y^*$ available online
- Objective for planning is approximated from current map

$$\epsilon_i = \mathcal{H}(\text{current loss in voxel } i)$$
Planning of depth measuring rays $J$

- No ground truth $y^*$ available online
- Objective for planning is approximated from current map

$$\epsilon_i = \mathcal{H}(\text{current loss in voxel } i) \times \prod_{j \in J} p_{ij} \quad \text{prob. that voxel } i \text{ is not visible by any ray } j \in J$$

Expected loss:

$$\epsilon_i \prod_{j \in J} p_{ij}$$
Planning of depth measuring rays $J$

- No ground truth $y^*$ available online
- Objective for planning is approximated from current map

\[ \epsilon_i = \mathcal{H}(\cdot) \times \prod_{j \in J} p_{ij} \]

… current loss in voxel $i$

… prob. that voxel $i$ is not visible by any ray $j \in J$

Total expected loss:

\[ \sum_{\text{voxels}} \epsilon_i \prod_{j \in J} p_{ij} \]
Planning of depth measuring rays $J$

- Planning of $J = \{J_1 \ldots J_L\}$ over horizon $L$ (i.e. for following positions $\ell = 1 \ldots L$):

$$\arg\min_J \sum_{\text{voxels}} \epsilon_i \prod_{j \in J} p_{ij} \text{ subject to } |J_\ell| \leq K$$

- Convex approximations
- Naive greedy algorithm
- Prioritized greedy algorithm
- Upper bound on the approximation ratio of prioritized greedy

\[ UB_{\text{proposed}}(\text{optimal}) \]

\[ 30\% \]

\[ 50\% \]
Experiment: Structure of 3D mapping network

input (320x320x32)
sparse voxel map

output (320x320x32)
probability of occupation

\[ \theta \in \mathcal{R}^{20M} \]
Experiment: Setting

- Steerable SSL is not yet available
- Simulation of SSL on Kitti dataset.
Experiment: Qualitative evaluation
Note: Detailed quantitative evaluation in poster and paper

Sparse measurements

Reconstructed map

Ground truth
Experiment: Summary & Questions