End-to-end Learning in Motion Planning for Robots

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Content of Paper

Abstract

Introduction

Method

Experiment

Conclusion

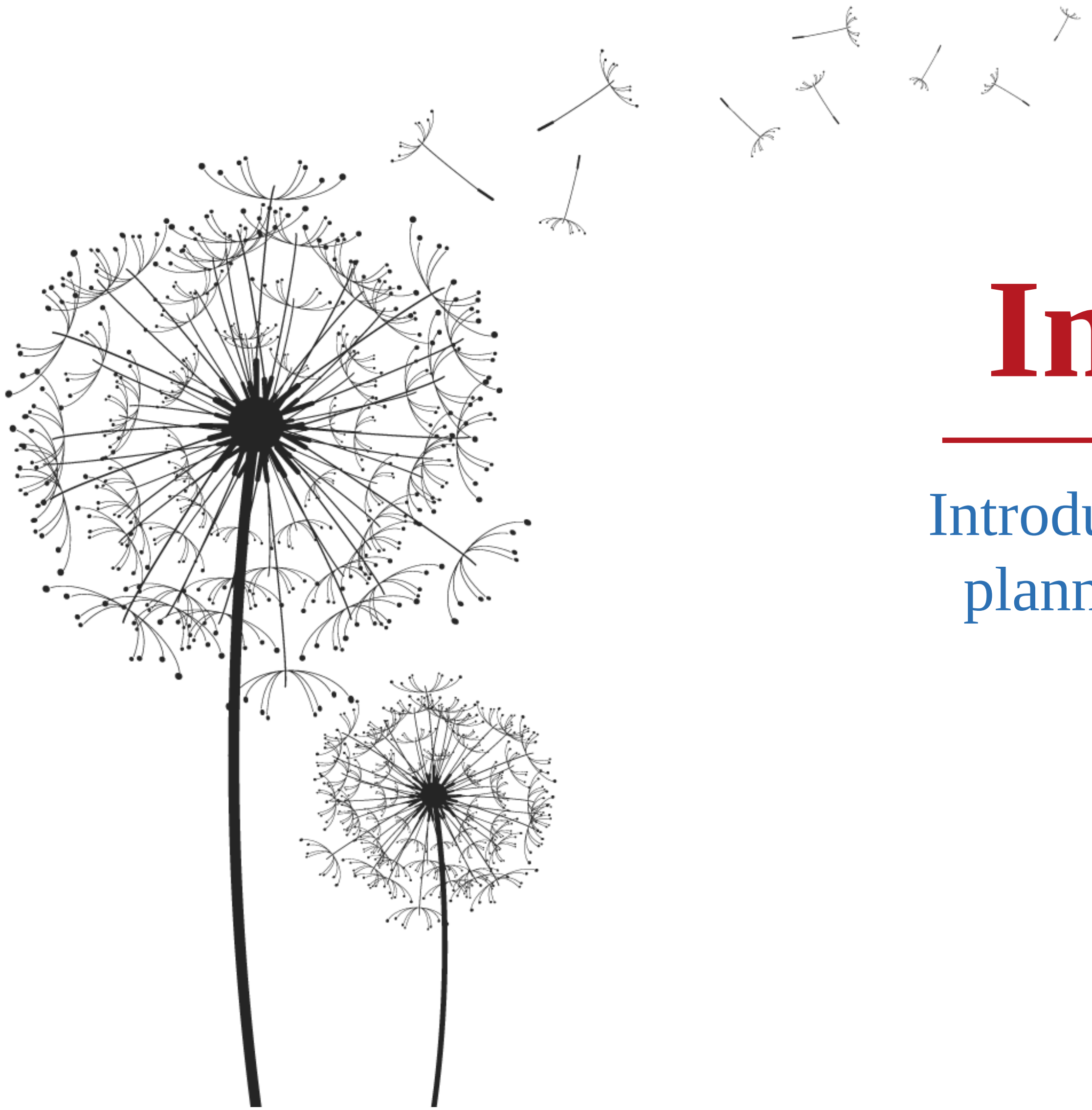
Abstract

The general meaning of the paper

Abstract

Learning from demonstration for motion planning is an ongoing research topic. In this paper we present a model that is able to learn the complex mapping from raw 2D laser range findings and a target position to the required steering commands for the robot. This approach learns a target oriented end-to-end navigation model for a robotic platform Furthermore, the supervised model training is based on expert demonstrations generated in simulation with an existing motion planner. We demonstrate that the learned navigation model is directly transferable to previously unseen virtual environments. It can safely navigate the robot through obstacle-cluttered environments to reach the desired targets.

Keywords*—motion planning, end-to-end navigation, supervised model training, expert demonstration*



Introduction

Introduce the background of motion planning and end-to-end learning

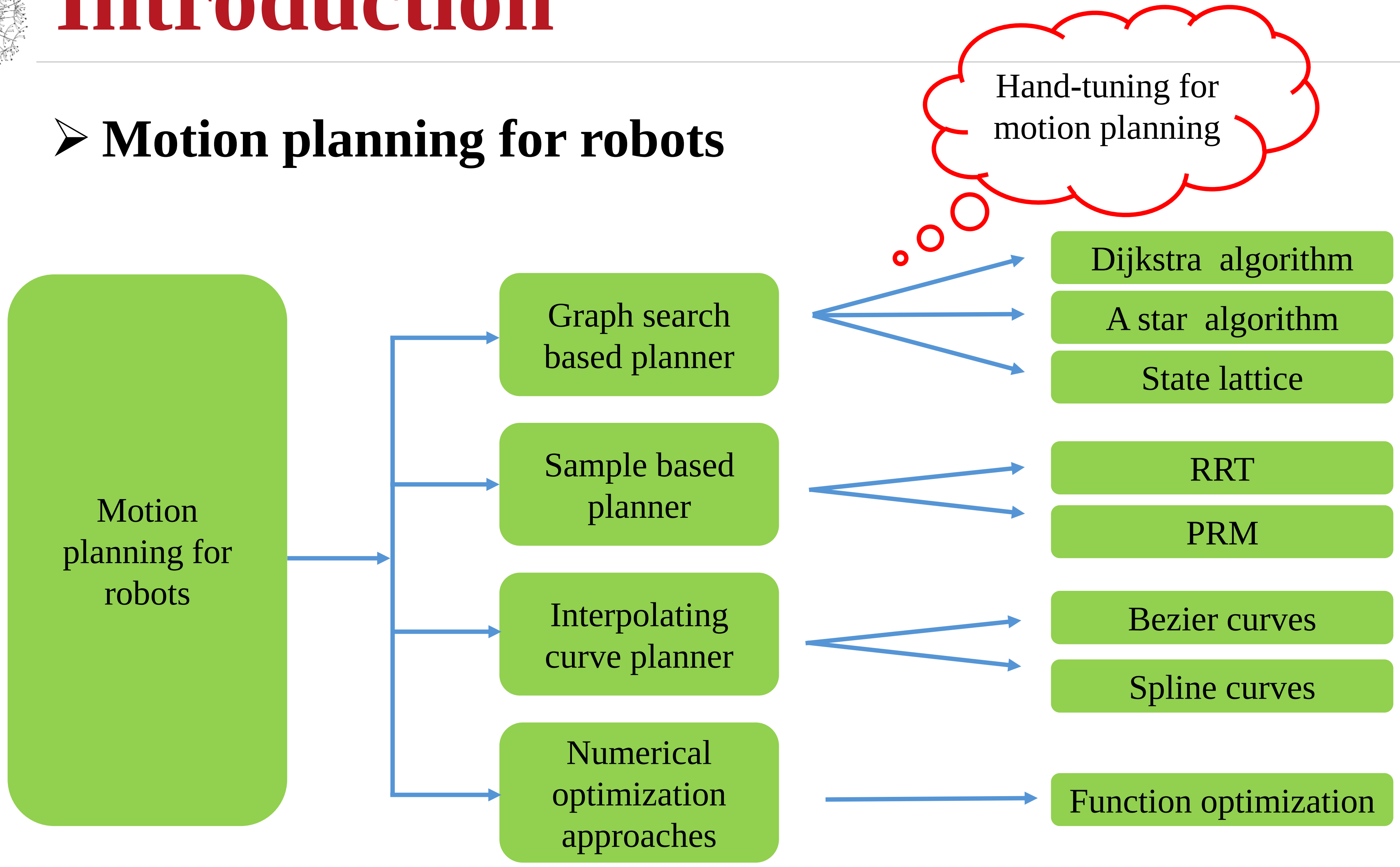
Introduction

➢ Application of mobile robots

- Cleaning robot
- Logistics robot
- Service robot

Introduction

➢ Motion planning for robots

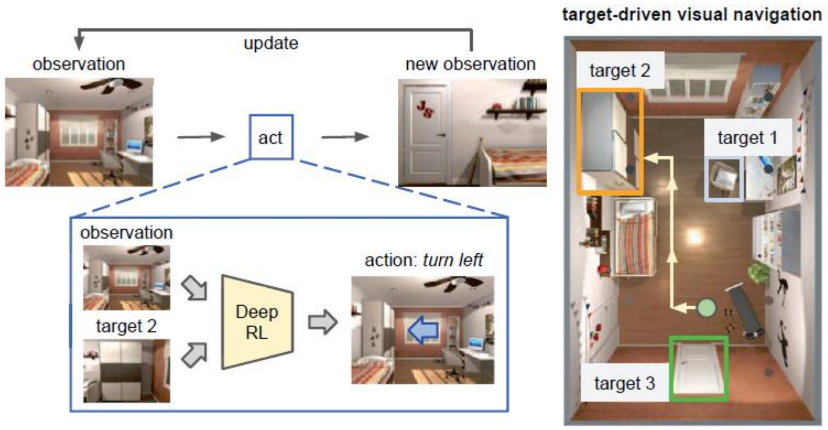


Introduction

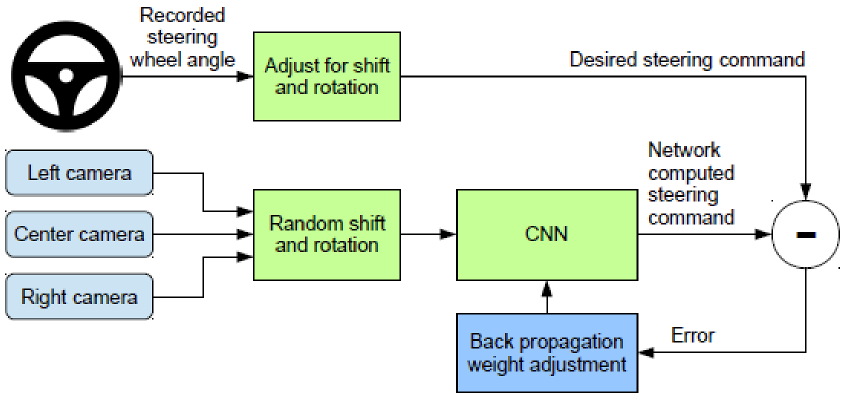
➢ End-to-end learning for robots

- Reduce hand-tuning
- Learning from expert operator
- Transfer the acquired knowledge to unseen environment

End-to-end learning for clutter environment



End-to-end learning for indoor navigation



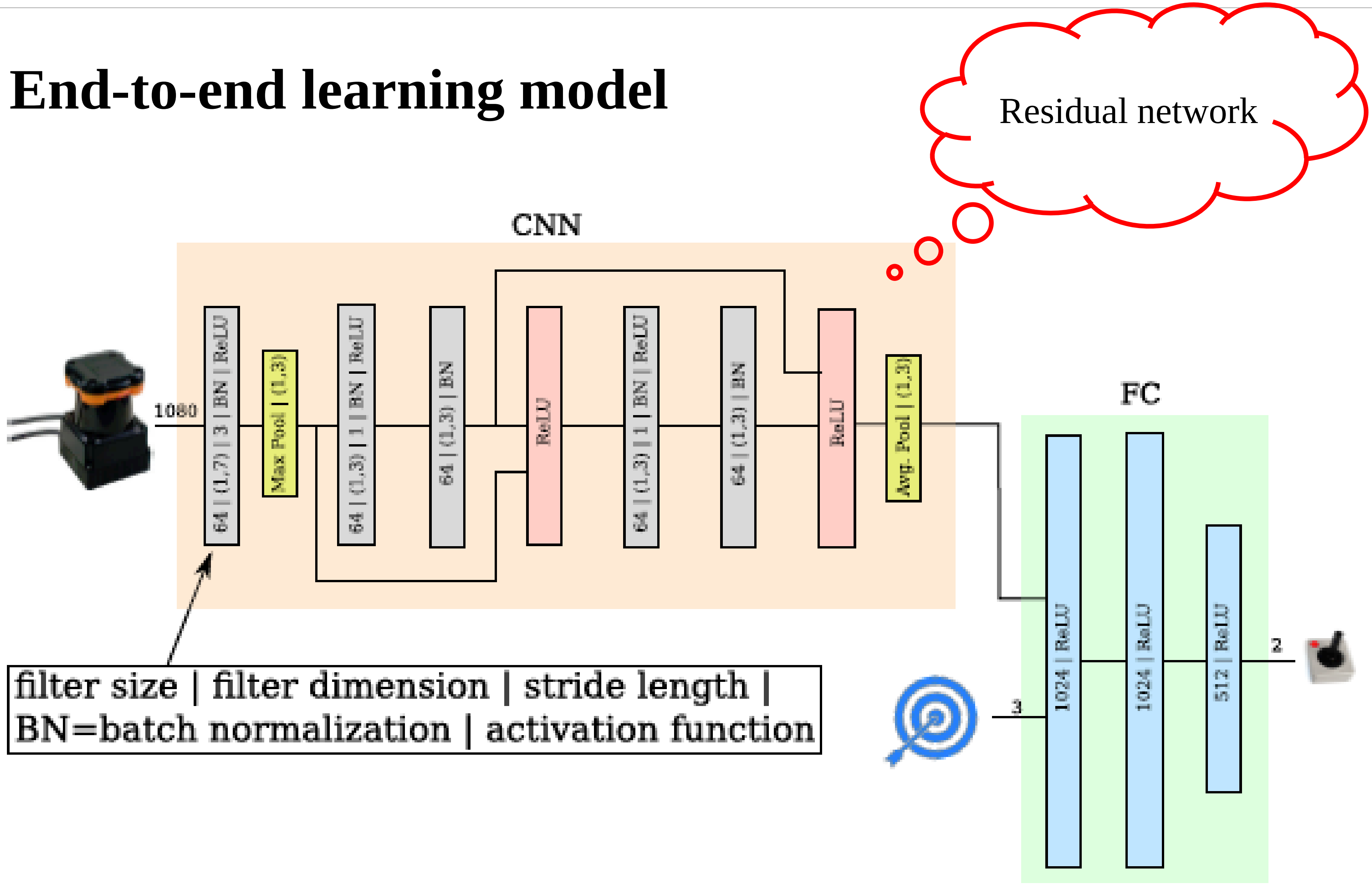
End-to-end learning for autonomous driving

Method

Set up the intercepting problem in a planar engagement

Method

➢ **End-to-end learning model**



Method

➢ Problem formulation

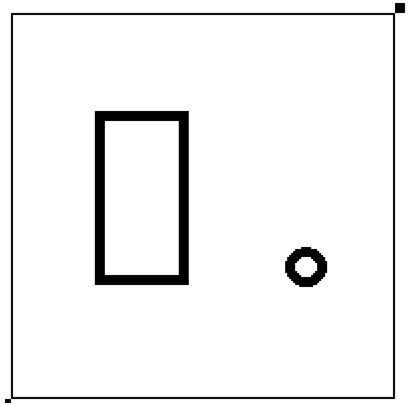
To find a predefined goal, we present an approach that directly computes suitable commands based on sensor and target data.
We try to find a function that directly maps a vector of sensor data y and goal information g to desired steering commands u

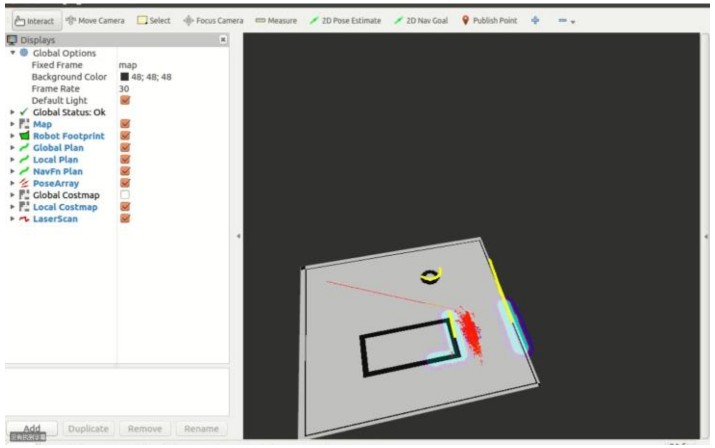
$$u = F_\theta(y, g)$$

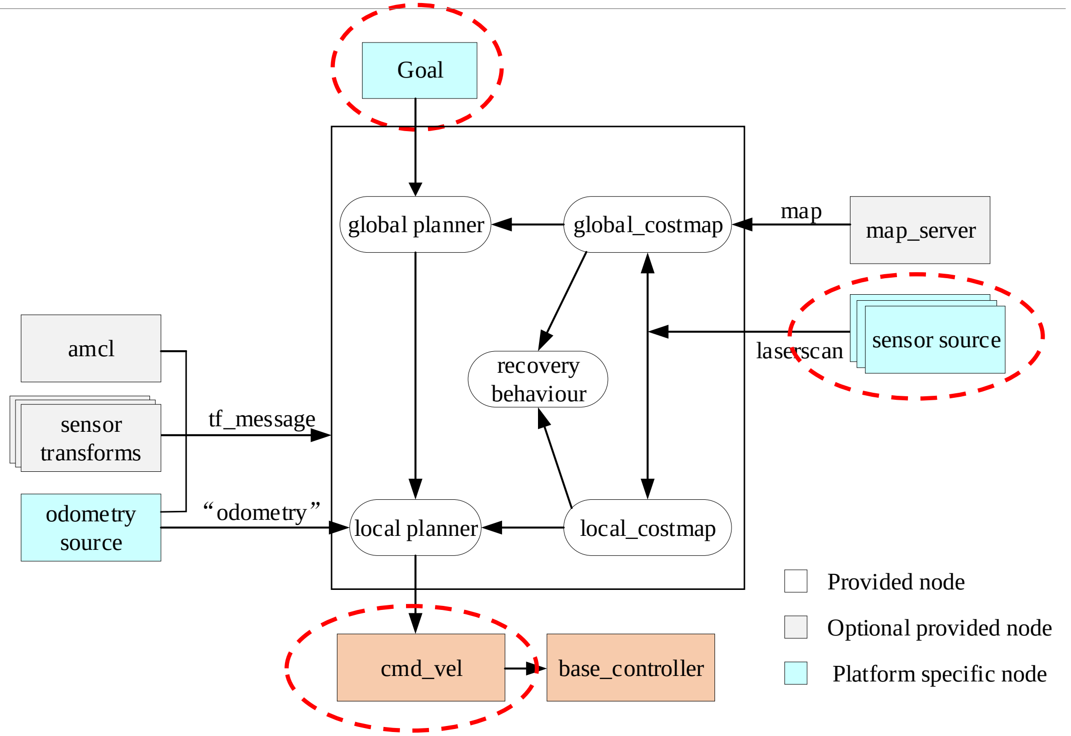
Given expert demonstrations u_{exp}, the optimization criterion is base on $\left|F_\theta(y, g) - u_{\exp}\right|$

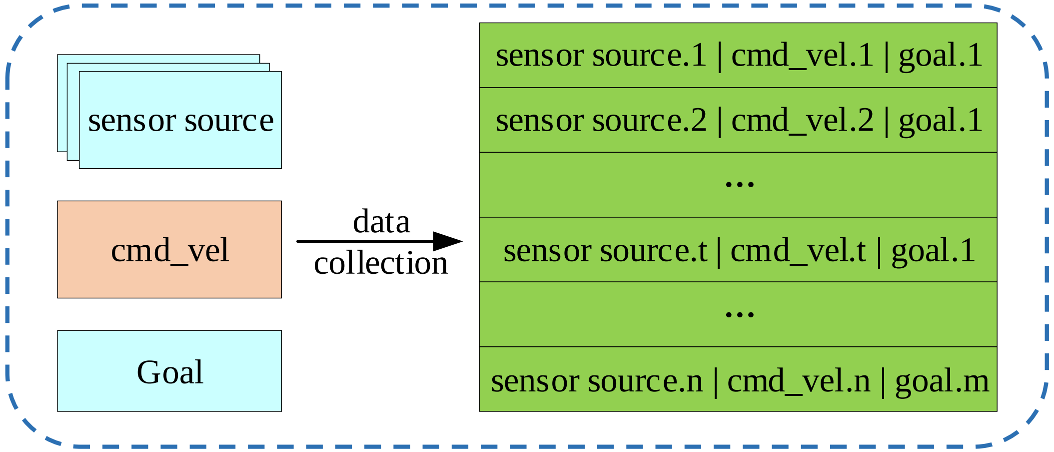
Method

➢ Data collection







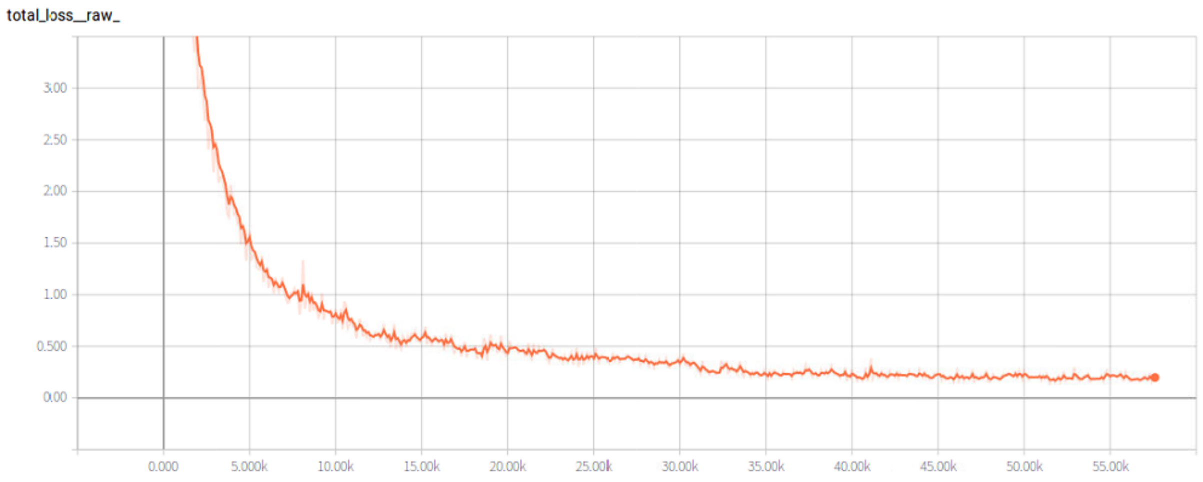


Method

➢ Model training

Use supervised learning approach to find the model parameter.
The optimization is conducted using the Adam optimizer with mini-batch training
The loss function for each supervised learning step is given by

$$J_k\left(\Gamma_B\right)=\frac{1}{N_B}\sum_{j=i}^{i+N_B}\left|F_{\theta_k}\left(y_i-g_i\right)-u_{\mathrm{exp},j}\right|$$



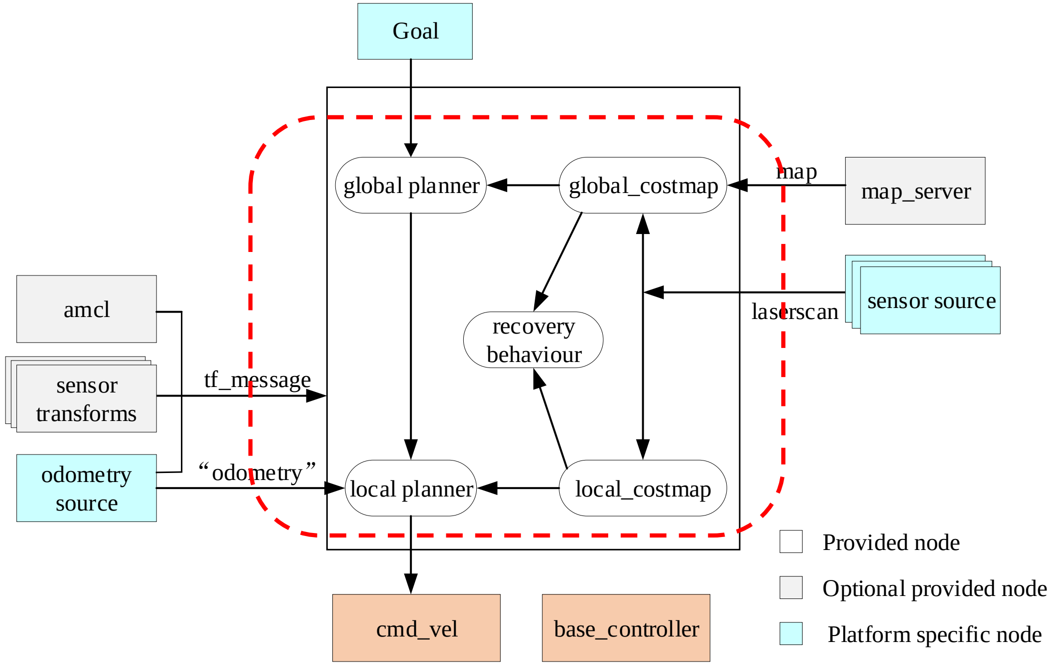
error=0.01

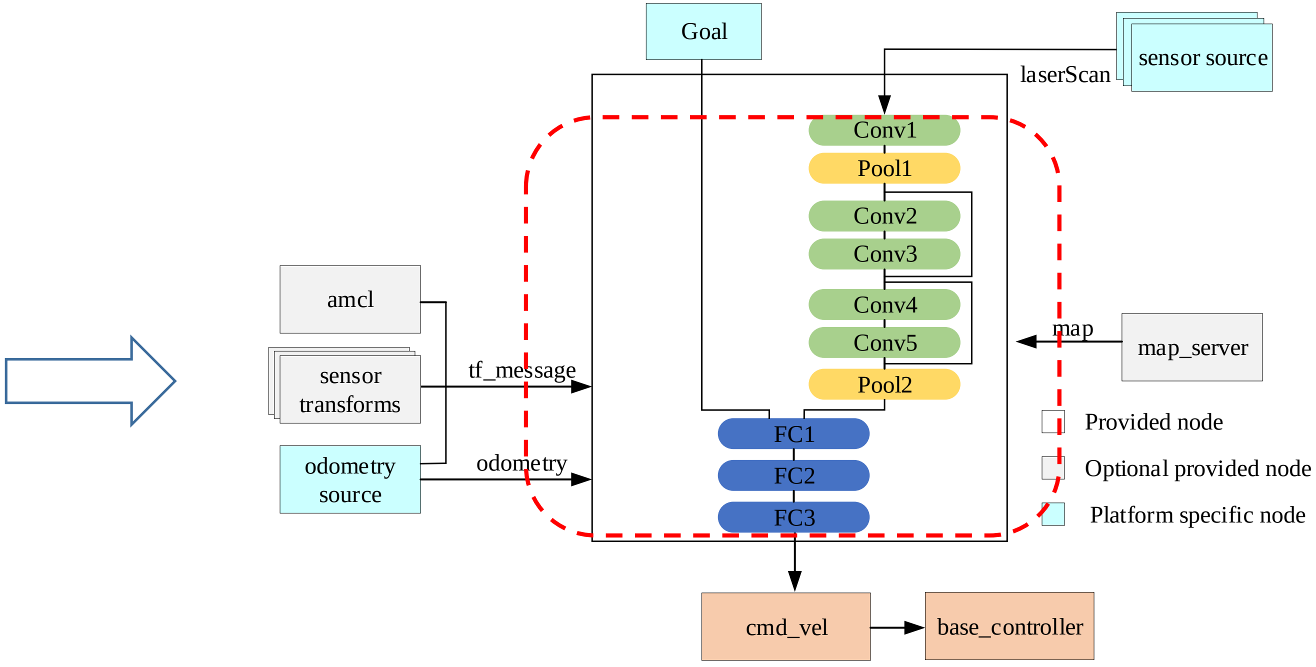
Experiment

Validate the performance of the motion planner

Experiment

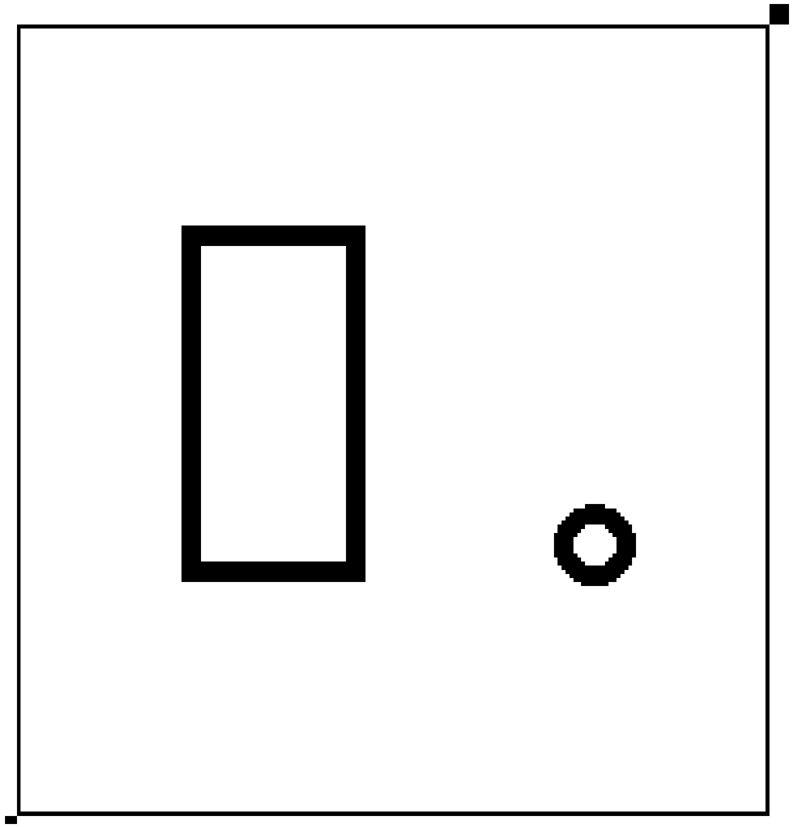
➢ Integrated with ROS navigation

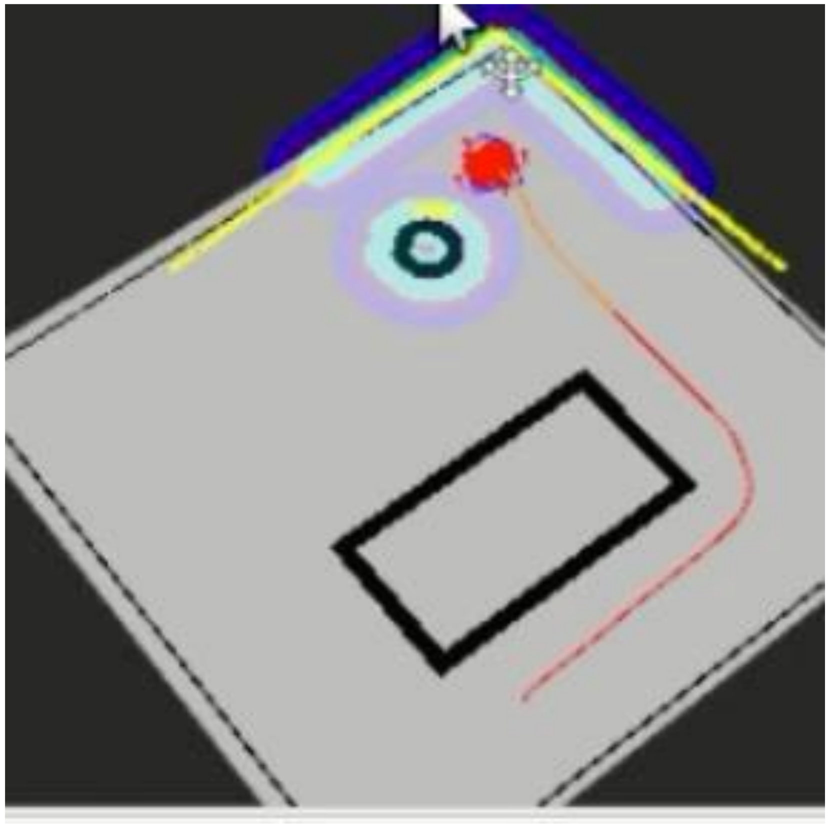




Experiment

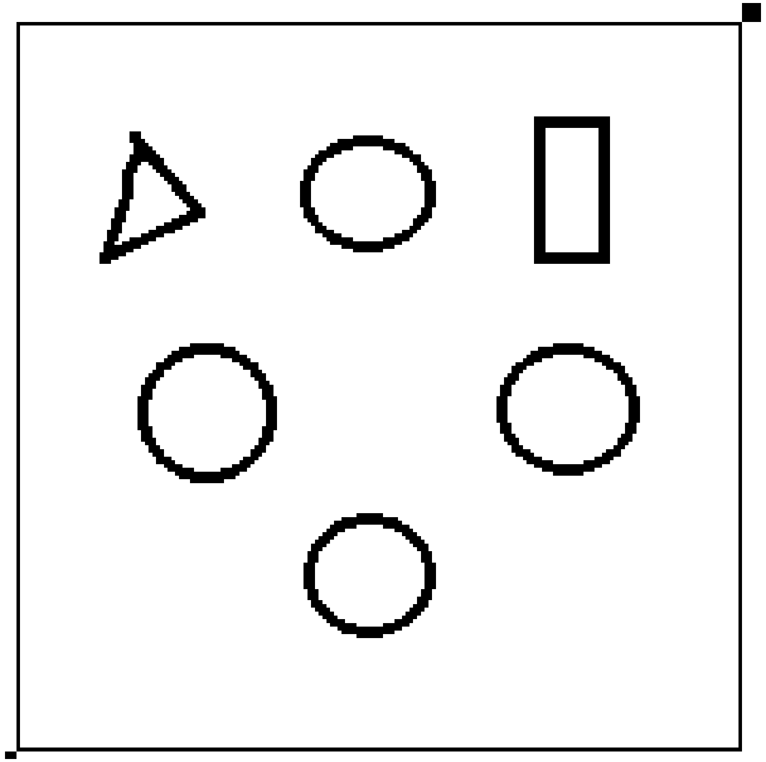
➤ 1) *Evaluation in training scenario*

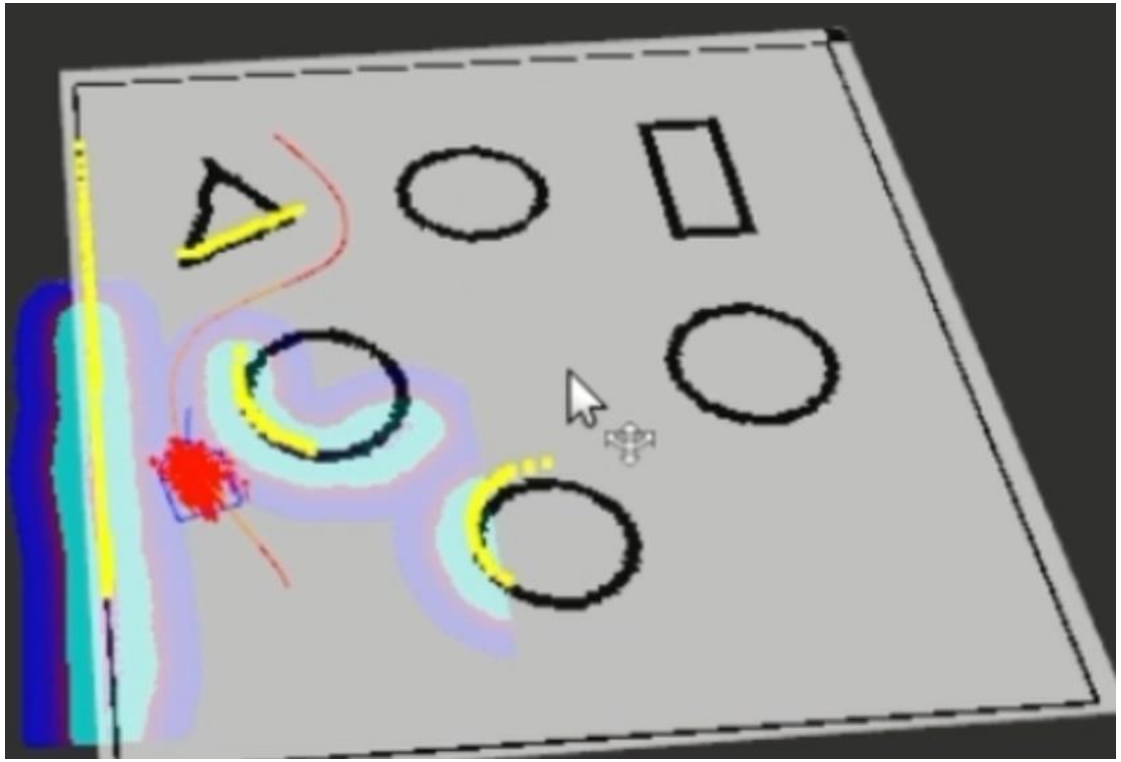




Experiment

➢ *2) Evaluation in unseen scenario*





Conclusion

Make a conclusion about the paper

Conclusion

01 A data-driven end-to-end motion planning approach

Given local laser range findings and a relative target position, our approach is able to compute the required steering commands for a navigation problem.

02 Disadvantages:

Our method needs expert demonstration which is expensive to get.

Once the robot enters a convex dead-end region, it is not capable of freeing itself.

03 Extension

Extend to autonomous driving using deep learning method with video data.

Conclusion

Related paper:

1. Pfeiffer M , Schaeuble M , Nieto J , et al. *From Perception to Decision: A Data-driven Approach to End-to-end Motion Planning for Autonomous Ground Robots[J]*. 2016.
2. Ross S , Melik-Barkhudarov N , Shankar K S , et al. *Learning Monocular Reactive UAV Control in Cluttered Natural Environments[J]*. 2012.
3. Zhu Y , Mottaghi R , Kolve E , et al. *Target-driven Visual Navigation in Indoor Scenes using Deep Reinforcement Learning[J]*. 2016.
4. Kim D K, Chen T. *Deep Neural Network for Real-time Autonomous Indoor Navigation[J]*. arXiv preprint arXiv:1511.04668, 2015.
5. Bojarski M, Del Testa D, Dworakowski D, et al. *End to end learning for self-driving cars[J]*. arXiv preprint arXiv:1604.07316, 2016.

Thank you!