

End-to-End Deep Neural Network Design for Short-term Path Planning

MQ Dao, D. Lanza, V. Fremont

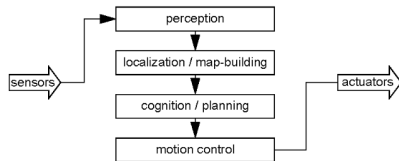
Monday, November 4, 2019

① Introduction

② Method

③ Performance

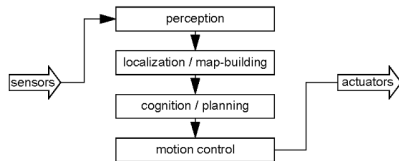
- Map-based navigation (R. Siegwart, I. R. Nourbakhsh, and D. Scaramuzza (2011). *Introduction to autonomous mobile robots.*)



See-think-act scheme

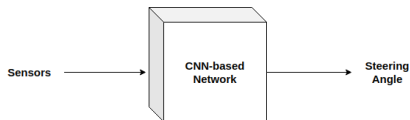
- End-to-end learning-based navigation

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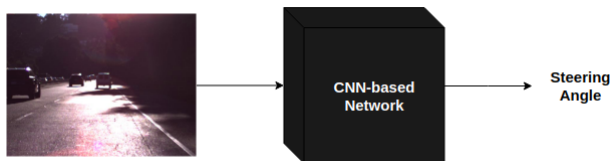
See-think-act scheme

- End-to-end learning-based navigation



End-to-end learning limitation

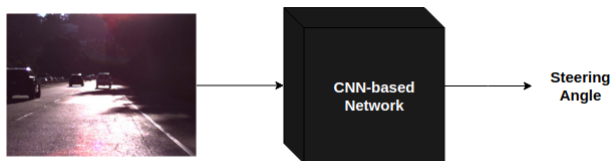
- No interpretable intermediate result



- Not able to predict vehicle speed

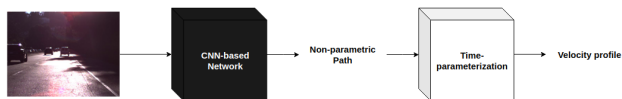
End-to-end learning limitation

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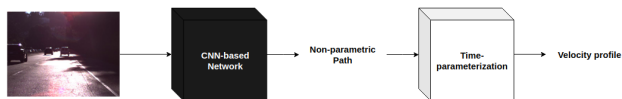
- Proposed solution for speed prediction



Motion planning pipeline for reactive navigation

- Advantage
 - Ease the need of using recurrent layers to learn vehicle speed
 - Able to account for dynamic constraint
 - Increase the reliability to the final output

- Proposed solution for speed prediction



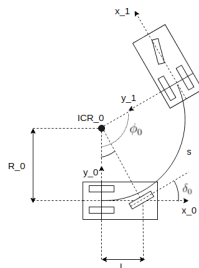
Motion planning pipeline for reactive navigation

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Formulation of learning problem

- Learning a path by learning a sequence of steering angle
[C. Hubschneider et al. \(2017\)](#). “Integrating end-to-end learned steering into probabilistic autonomous driving”. In: *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*

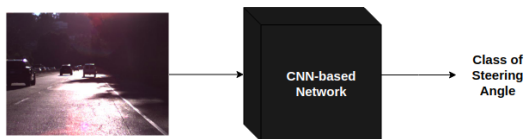
$$\text{Path} = [\delta_0, \delta_1, \dots, \delta_n] \quad (1)$$



Relation between 2 consecutive waypoints

Formulation of learning problem

- Learning a path by learning a sequence of steering angle
- Learning a classifier for steering angle prediction



A class spans an 1-degree interval of the steering angle range

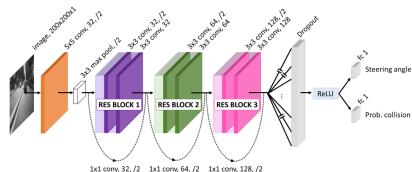
Model Architecture

- DroNet architecture [A. Loquercio et al. \(2018\)](#). “DroNet: Learning to Fly by Driving”. In: *IEEE Robotics and Automation Letters*

- Our architecture: ResNet body + 5 classifiers made of 2 dense layers

Model Architecture

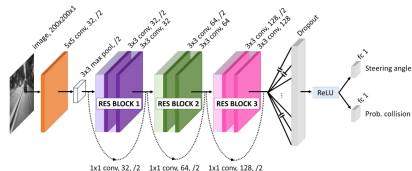
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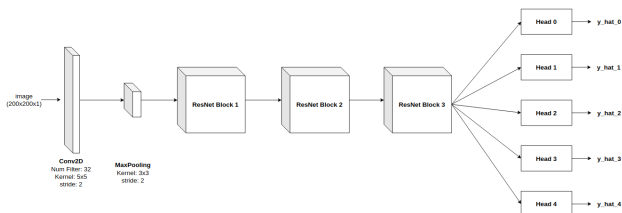
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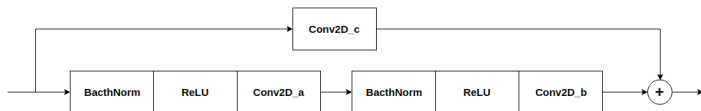


- Our architecture: ResNet body + 5 classifiers made of 2 dense layers



Model Architecture

- Detail of ResNet body [A. Loquercio et al. \(2018\)](#). “DroNet: Learning to Fly by Driving”. In: *IEEE Robotics and Automation Letters*



Stage	Layer	Number of kernels	Kernel size	Stride Stride	Padding Padding
1	Conv2D_a	32	3	2	same
1	Conv2D_b	32	3	1	same
1	Conv2D_c	32	1	2	same
2	Conv2D_a	64	3	2	same
2	Conv2D_b	64	3	1	same
2	Conv2D_c	64	1	2	same
3	Conv2D_a	128	3	2	same
3	Conv2D_b	128	3	1	same
3	Conv2D_c	128	1	2	same

Dataset

- Udacity dataset

- Expected input - output

Dataset

- Udacity dataset



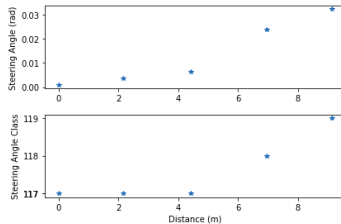
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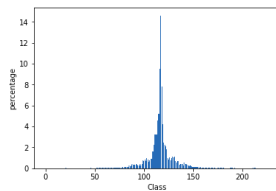
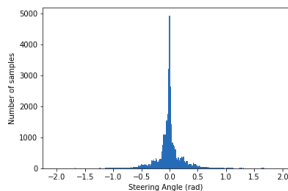


- Expected input - output

**x****y**

Handling dataset imbalance

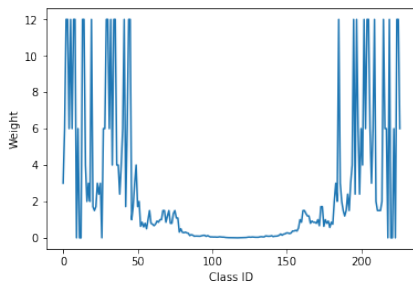
- The dominance of classes corresponding to small steering angles due to the lack of sharp turns



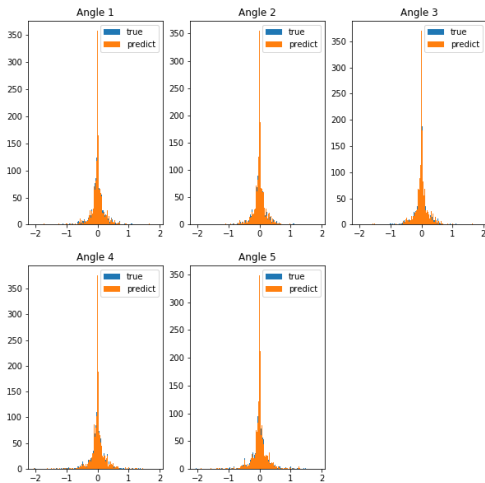
Handling dataset imbalance

- The dominance of classes corresponding to small steering angles
- Class weight calculated by median frequency balancing

$$w(i) = \frac{\text{median frequency of the dataset}}{\text{frequency of this class}} \quad (2)$$



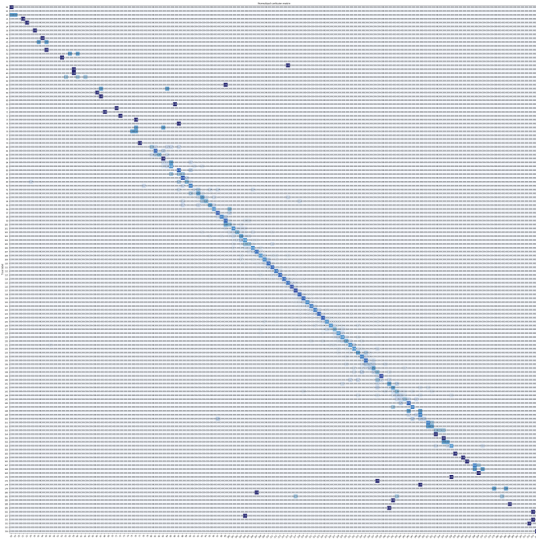
Predicted angle distributions



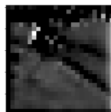
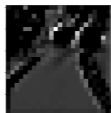
RMSE and EVA Comparison

Model	RMSE	EVA
Constant baseline	0.2129	0
Random baseline	0.3 ± 0.001	-1.0 ± 0.022
DroNet	0.1090	0.7370
Event-based Model	0.0716	0.8260
Head_0	0.0869	0.8933
Head_1	0.0920	0.8781
Head_2	0.1052	0.8382
Head_3	0.0820	0.9012
Head_4	0.0851	0.8943

Confusion Matrix of the 1st Classifier



ResNet Blocks Output



Input image

1st Block

2nd Block

3rd Block

Demonstration Video

- Learn human driving behavior through a classification problem

- Learned non-parameterized path can be integrated into trajectory planning framework

- Improve the classification accuracy
- Implement the trajectory optimization to timestamp the path
- Evaluate the performance on a real autonomous vehicle