PolyLaneNet:
Lane Estimation via Deep Polynomial Regression

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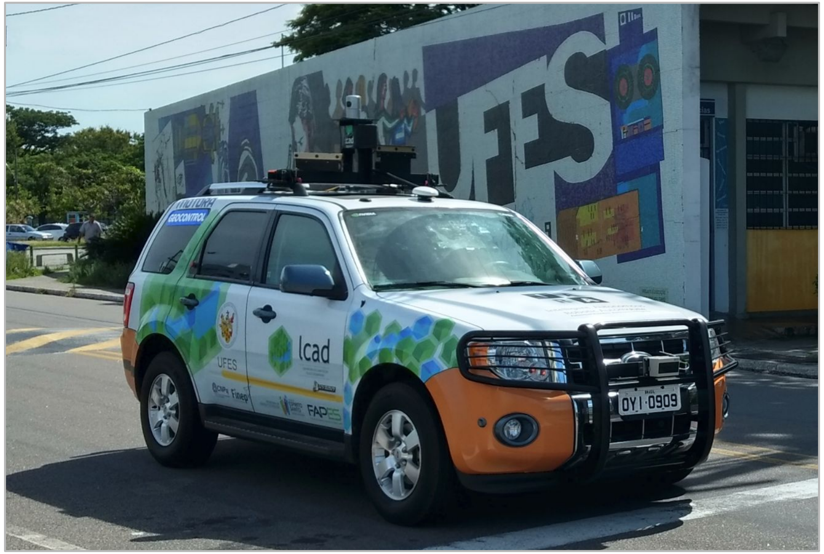
CAPES

Outline

- Introduction
- Motivation
- Related work
- Proposed method: PolyLaneNet
- Experiments
- Results
- Conclusion

Introduction

- Autonomous vehicles
- Advanced driver-assistance systems
- Lane detection



Motivation

Real-world scenarios difficulties

Occlusion, worn out road markings, etc

Current methods may not be fast enough

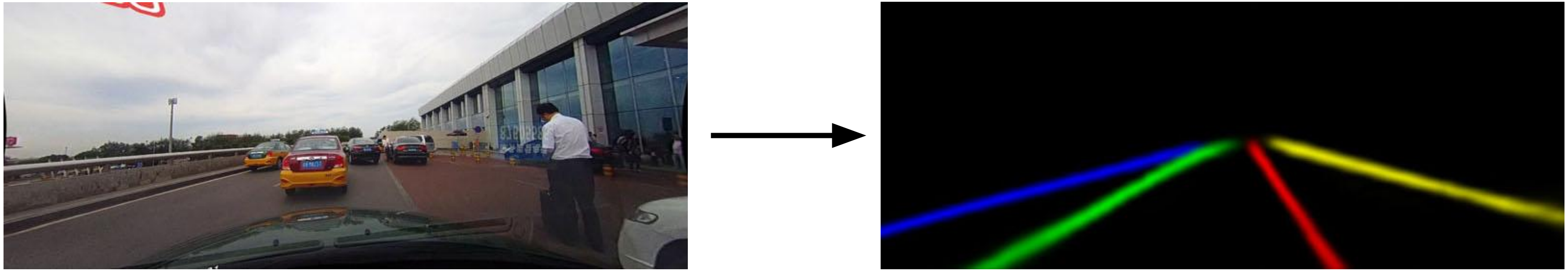
In some applications, a faster than real-time efficiency is required to save resources for other systems

Reproducing results from other works is not easy

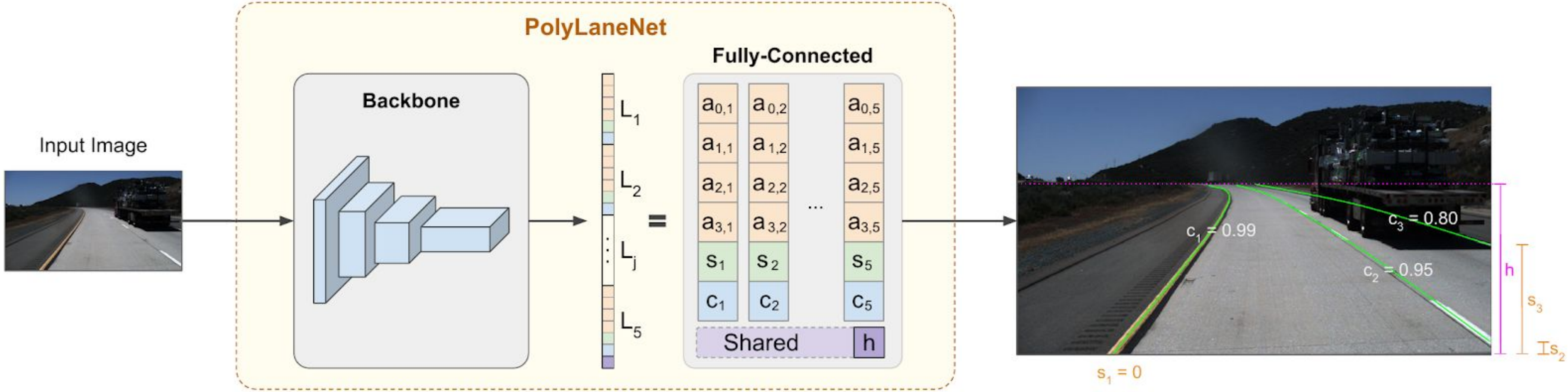
Most works in the topic do not publish the source code

Related Work

- Traditional computer vision methods
- Segmentation-based methods
- Other approaches, such as anchor-based methods



PolyLaneNet



Training PolyLaneNet

- M_{max} lanes predicted, each with
  - A confidence probability c_j
  - Vertical offset s_j
  - Polynomial coefficients P_j
- Horizon vertical offset h
- Predictions and GT are matched by sorting according to the bottom position

$$\begin{aligned} L(\{\mathcal{P}_j\}, h, \{s_j\}, \{c_j\}) = & W_p L_p(\{\mathcal{P}_j\}, \{\mathcal{L}_j^*\}) \\ & + W_s \frac{1}{M} \sum_j L_{reg}(s_j, s_j^*) \\ & + W_c \frac{1}{M} \sum_j L_{cls}(c_j, c_j^*) \\ & + W_h L_{reg}(h, h^*), \end{aligned}$$

Datasets

Dataset	Train	Validation	Test
TuSimple	3,268	358	2,782
LLAMAS	58,269	20,844	20,929
ELAS	11,036	—	5,957

Metrics

- Accuracy:

$$Acc(\mathcal{P}_j, \mathcal{L}_j^*) = \frac{1}{|\mathcal{L}_j^*|} \sum_{(x_{i,j}^*, y_{i,j}^*) \in \mathcal{L}_j^*} \mathbf{1}[|p_j(y_{i,j}^*) - x_{i,j}^*| < \tau_{acc}]$$

- FP: rate of predictions with Acc smaller than 85%
- FN: rate of GTs with corresponding predictions with Acc smaller than 85%
- We also propose using LPD, a more robust metric proposed by (Satzoda & Trivedi, 2014)
- Acc is more permissive, while LPD captures better the accuracy of a prediction on both the near and far depths of view of the ego-vehicle

State-of-the-art comparison

- TuSimple testing set

Method	Acc (%)	FP	FN	FPS	MACs	PP
Line-CNN	96.87	0.0442	0.0197	30		
ENet-SAD	96.64	0.0602	0.0205	75		✓
SCNN	96.53	0.0617	0.0180	7		✓
FastDraw	95.20	0.0760	0.0450	90		✓
PolyLaneNet	93.36	0.0942	0.0933	115	1.748 G	

Ablation Study - Polynomial Degree

- TuSimple validation set

Degree	Acc	FP	FN	LPD
1st	88.63	0.2231	0.1865	2.532
2nd	88.89	0.2223	0.1890	2.316
3rd	88.62	0.2237	0.1844	2.314

Ablation Study - Polynomial Degree

- **Upperbound** of polynomials on the TuSimple validation set

Degree	Acc	FP	FN	LPD
1st	96.22	0.0393	0.0367	1.512
2nd	97.25	0.0191	0.0175	1.116
3rd	97.84	0.0016	0.0014	0.732
4th	98.00	0.0000	0.0000	0.497
5th	98.03	0.0000	0.0000	0.382

Ablation Study - Backbone and input size

- TuSimple validation set

Modification		Acc	FP	FN	MACs (G)
Backbone	ResNet-34	88.07	0.2267	0.1953	17.154
	ResNet-50	83.37	0.3472	0.3122	19.135
	EfficientNet-b1	**89.20**	**0.2170**	**0.1785**	2.583
	EfficientNet-b0	88.62	0.2237	0.1844	1.748
Input size	320x180	85.45	0.2424	0.2446	0.396
	480x270	88.39	0.2398	0.1960	0.961
	640x360	**88.62**	**0.2237**	**0.1844**	1.748

Ablation Study - Others

- TuSimple validation set

Modification		Acc	FP	FN
Top-Y sharing	No	88.43	0.2126	0.1783
	Yes	88.62	0.2237	0.1844
Pretraining	None	84.37	0.3317	0.2826
	ImageNet	88.62	0.2237	0.1844
Data Augmentation	None	78.63	0.4788	0.4048
	10x	88.62	0.2237	0.1844

Qualitative results - TuSimple

Qualitative results - LLAMAS

Qualitative results - ELAS

Conclusion

- Problems in current datasets and metrics were highlighted
- A simple and efficient model was proposed
- Competitive accuracy compared to state-of-the-art-methods
- Source code is public: github.com/lucastabelini/PolyLaneNet