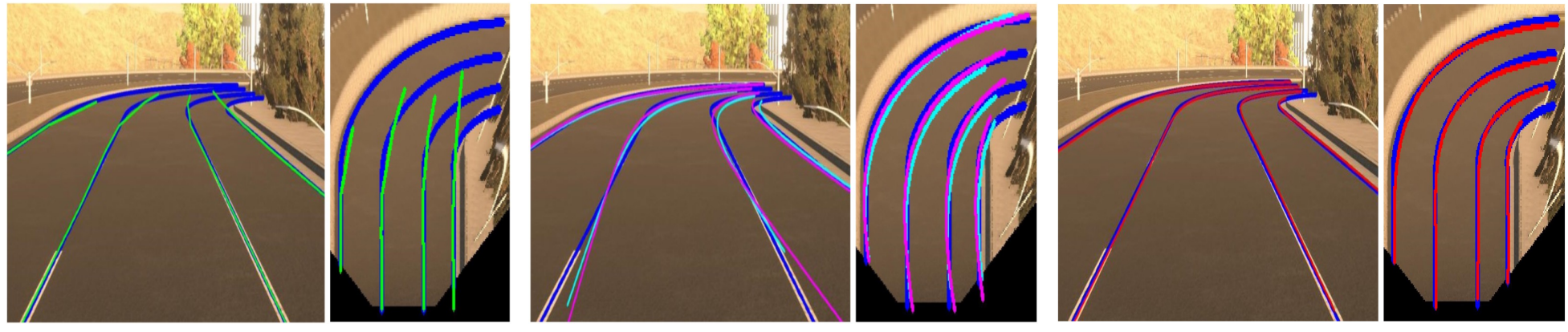


I. Motivation and Contributions

Abstract. We present a method to detect 3D traffic lines from single RGB images. To overcome limitations of discrete anchor- or grid-based approaches we propose a parametric lane representation based on sophisticated B-Splines.

Lane detections using different representations for typical road shape



Anchor-based (Gen-LaneNet [2])

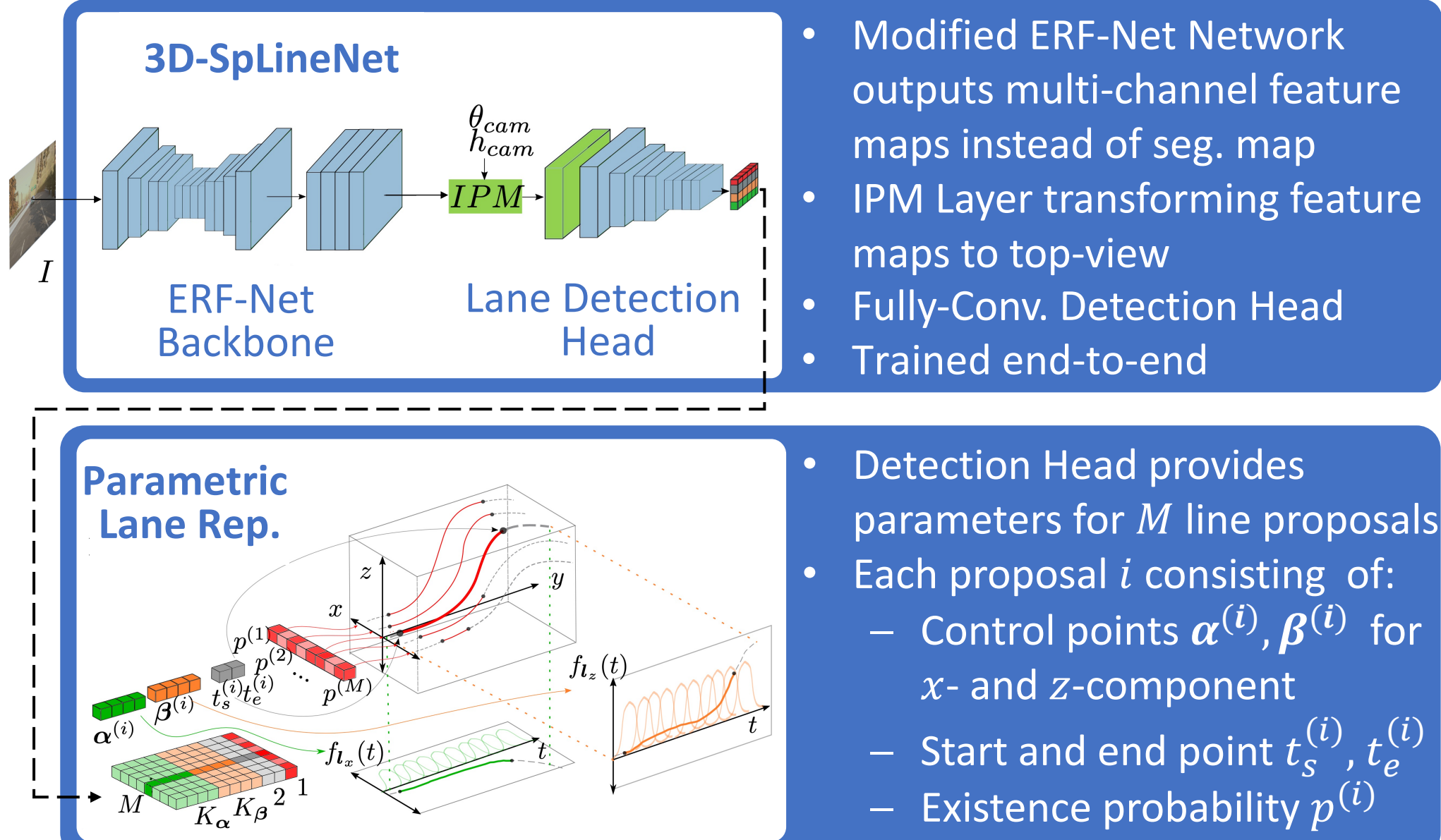
Polynomials of 3rd and 5th degree

B-Splines of 3rd degree

- Discrete / not smooth
- Requires high degrees for simple road shapes
- Benefits of parametric representations
- Fail for strong deviations from anchor
- Not suited for lanes
- Suited for typical roads

- Contributions**
- A **new representation** to model 3D lanes with parametric B-Splines
 - An end-to-end-trainable detection network called **3D-SpLineNet**
 - SOTA performance** on Apollo 3D Lanes Synthetic benchmark

II. Overview of Method



III. Parametric Representation

3D Lane Representation

$$\mathbf{l}(t) = \begin{pmatrix} x(t) \\ y(t) \\ z(t) \end{pmatrix} = \boldsymbol{\eta} \odot \begin{pmatrix} f_{l_x}(t) \\ t \\ f_{l_z}(t) \end{pmatrix}$$

Normalization vector

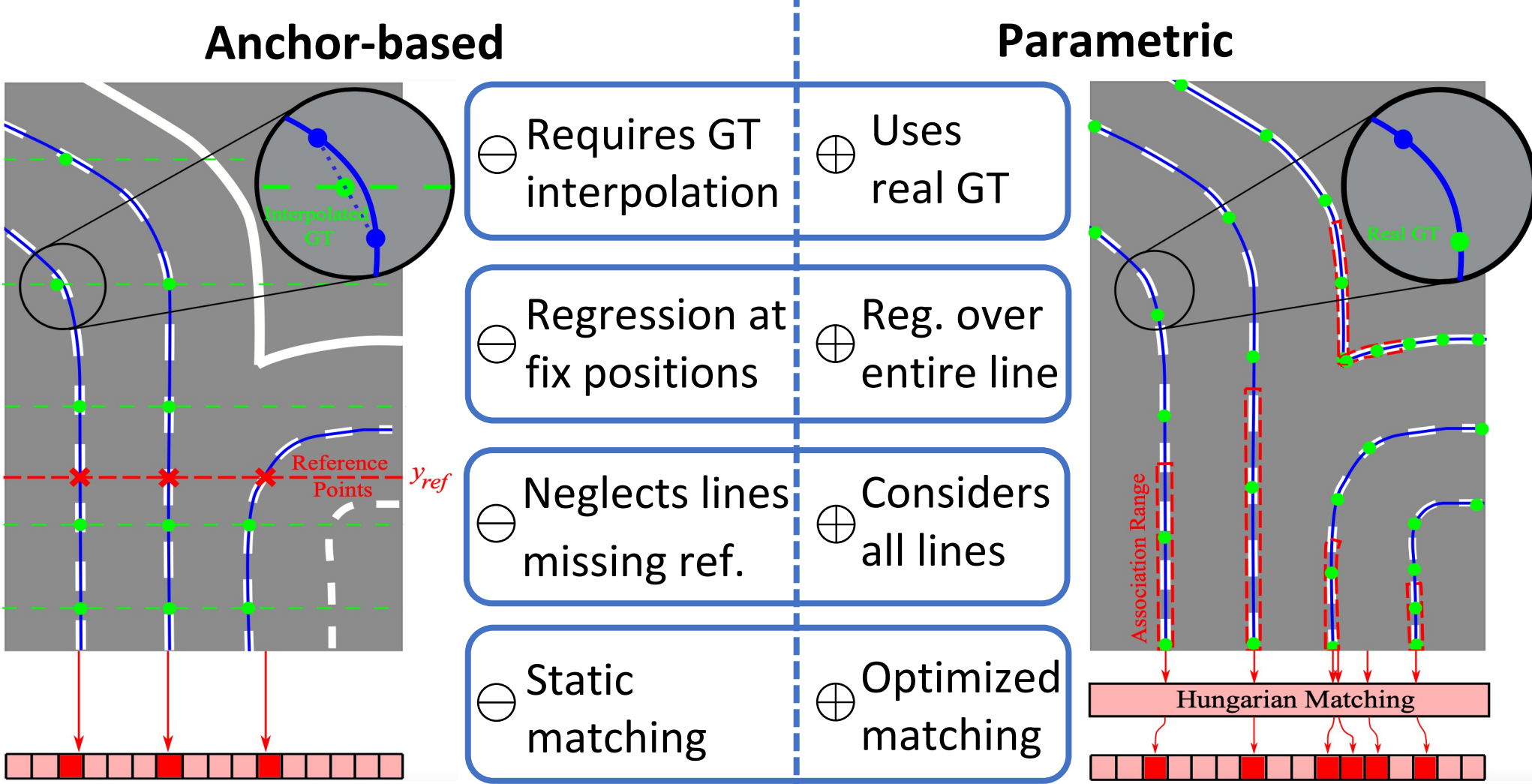
$$\boldsymbol{\eta} = \begin{pmatrix} x_{max} \\ y_{max} \\ z_{max} \end{pmatrix}$$

x-comp $f_{l_x}(t) = \sum_{k=1}^{K_B} \alpha_k \cdot B_{k,d}(t)$

z-comp $f_{l_z}(t) = \sum_{k=1}^{K_B} \beta_k \cdot B_{k,d}(t)$

Start- / end-point

$$t \in [t_s, t_e]$$



IV. Training Objective

Classification loss $\mathcal{L}_c = - \sum_{i=1}^M \hat{p}^{(i)} \log p^{(i)} + (1 - \hat{p}^{(i)}) \log(1 - p^{(i)})$

Shape matching loss $\mathcal{L}_s = \int_{\hat{t}_s}^{\hat{t}_e} \|\mathbf{w}(t) \odot (\mathbf{f}_l(t) - \boldsymbol{\eta}^{-1} \odot \hat{\mathbf{l}}(t))\|_1 dt$

Range loss $\mathcal{L}_r = |t_s - \hat{t}_s| + |t_e - \hat{t}_e|$, with $t_s < t_e$

Final loss function $\mathcal{L} = \lambda_c \cdot \mathcal{L}_c + \sum_{i=1}^M \hat{p}^{(i)} \cdot (\lambda_s \cdot \mathcal{L}_s^{(i)} + \lambda_r \cdot \mathcal{L}_r^{(i)})$

V. Comparison to State-of-the-art

Quantitative Evaluation

on Apollo 3D Lanes Synthetic dataset [2]

Detection Perf. / Geometric Acc.

- Outperforming anchor-based on all test sets
- Strong gap in detection rate even on complex Rare Scenes set
- Lower geometric errors wrt. almost all criteria
- Room for improvement for far-range z-error → Architecture / IPM

Method	F	AP	x-error		z-error	
			near	far	near	far
3D-L.[1]	86.4	89.3	6.8	47.7	1.5	20.2
Gen-L[2]	88.1	90.1	6.1	49.6	1.2	21.4
Ours	96.3	98.1	3.7	32.4	0.9	21.3

Standard test set

3D-L.	72.0	74.6	16.6	85.5	3.9	52.1
Gen-L.	78.0	79.0	13.9	90.3	3.0	53.9
Ours	92.9	94.8	7.7	69.9	2.1	56.2

Rare Scenes test set

3D-L.	72.5	74.9	11.5	60.1	3.2	23.0
Gen-L.	85.3	87.2	7.4	53.8	1.5	23.2
Ours f.b.	91.3	93.1	6.9	46.8	1.3	24.8

Visual Variations test set

Runtime

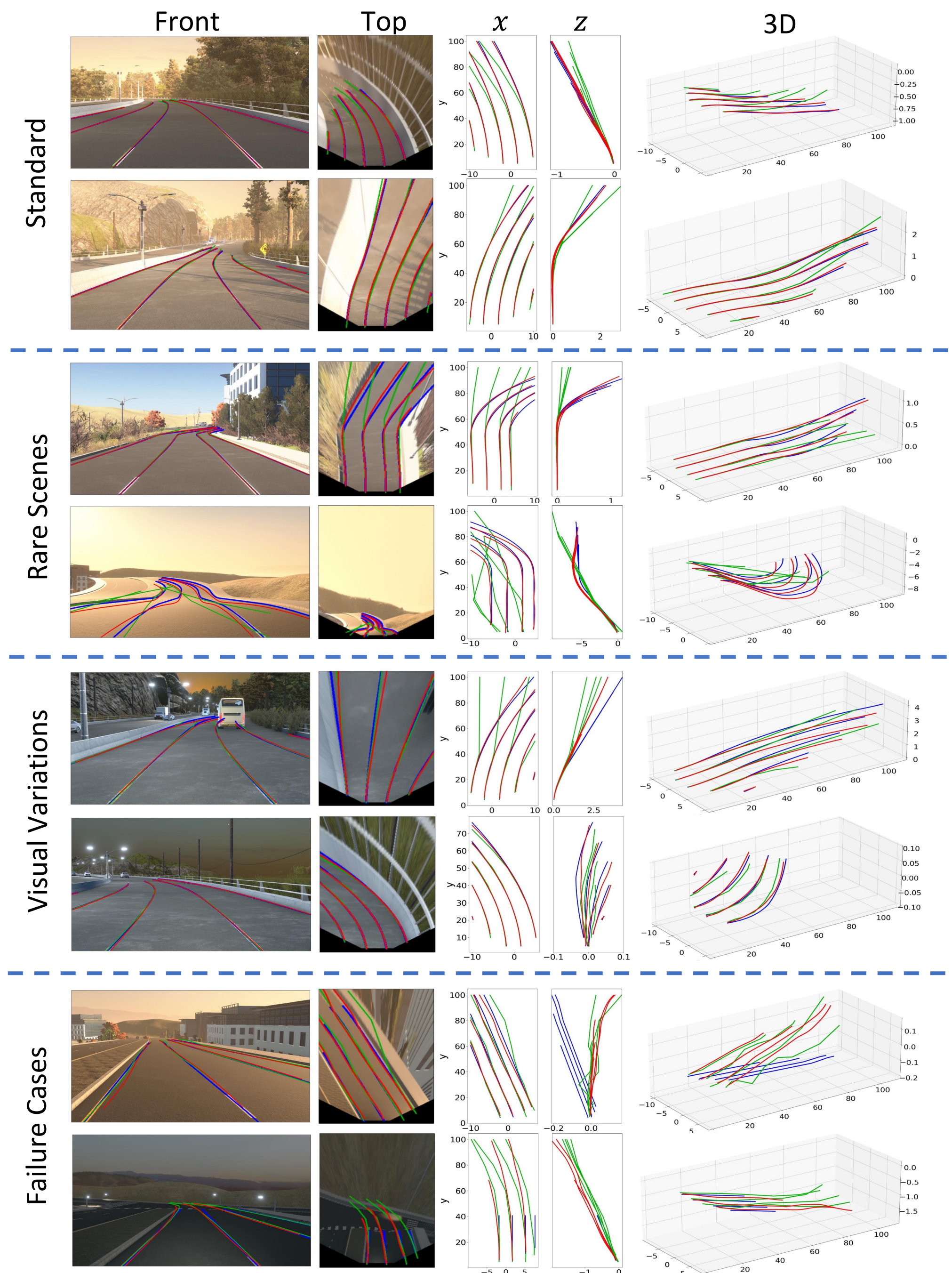
- No time consuming post-processing required
- Faster inference than discrete representations

Method	3D-L.	Gen-L.	Ours
Runtime	41.9 fps	36.3 fps	74.3 fps

All methods evaluated on NVIDIA GeForce Titan X

Qualitative Evaluation

- Ground truth - Gen-LaneNet - 3D-SpLineNet



VI. Ablation Studies

Association Criterion

- Association range matching surpassing fixed ref. point
- Best results for 40 %

Ref.	20 m	First 20 %	First 40 %	100 %
F	90.7 %	92.1 %	92.9 %	91.2 %
AP	92.5 %	94.1 %	94.8 %	93.4 %

Analysis of Representations

- Polynomials of degree 2-3 not sufficient
- 3rd degree splines sufficient even for few knots
- Impact of knot number decreases for higher values → 5 knots sufficient

Rep.	d	N	F	x-error		z-error	
				near	far	near	far
Poly.	2	—	88.0	14.0	83.1	2.4	58.1
	3	—	90.4	13.6	75.4	2.6	57.3
	5	—	91.6	9.6	74.8	2.4	58.2
B-Sp.	1	3	81.3	26.3	102.3	3.0	58.1
	3	3	90.8	9.9	69.7	2.4	56.4
	3	5	92.5	8.2	68.3	2.2	56.
	1	10	91.5	9.1	71.3	2.2	56.3
	3	10	92.1	8.3	70.8	1.8	56.3
	1	15	91.6	9.1	69.1	1.9	54.9
	3	15	92.9	7.7	69.9	2.1	56.2

VII. Conclusion and Future Work

In summary:

- Parametric representations show benefits over discrete anchor-based
- B-Splines of 3rd degree sufficient to model complex road shapes
- SOTA performance of 3D-SpLineNet

In future we investigate:

- Ways to improve height estimation
- Better initialization strategies with 3-component representation
- Weakly supervised approaches using 2D ground truth

[1] Noa Garnett, Rafi Cohen, Tomer Pe'er, Roei Lahav, and Dan Levi. 3d-lanenet: End-to-end 3d multiple lane detection. In *Proc. of the IEEE International Conf. on Computer Vision (ICCV)*, 2019.

[2] Yuliang Guo, Guang Chen, Peitao Zhao, Weide Zhang, Jing-hao Miao, Jingao Wang, and Tae Eun Choe. Gen-lanenet: A generalized and scalable approach for 3d lane detection. In *Proc. of the European Conf. on Computer Vision (ECCV)*, 2020.