Iterative Camera-LiDAR Extrinsic Optimization via Surrogate Diffusion

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Introduction

Single-Step Model → Multi-Step Model

Naive Iteration: In each iteration, the input to the next iteration is generated by left-multiplying the model output with the input of the current iteration.
Multi-Range iteration: Similar to straightforward iteration, except that a different model is employed at each iteration, specialized for a specific error range.
Internal: Iterative updates of the extrinsics are performed within an *internal* recurrent architecture (e.g., LSTM or GRU), which exploits sequential dependencies.
Diffusion: The diffusion process progressively adds noise to the ground-truth extrinsic matrix to generate an initial noisy estimate, while the denoising process reverses this procedure through a surrogate calibration model.

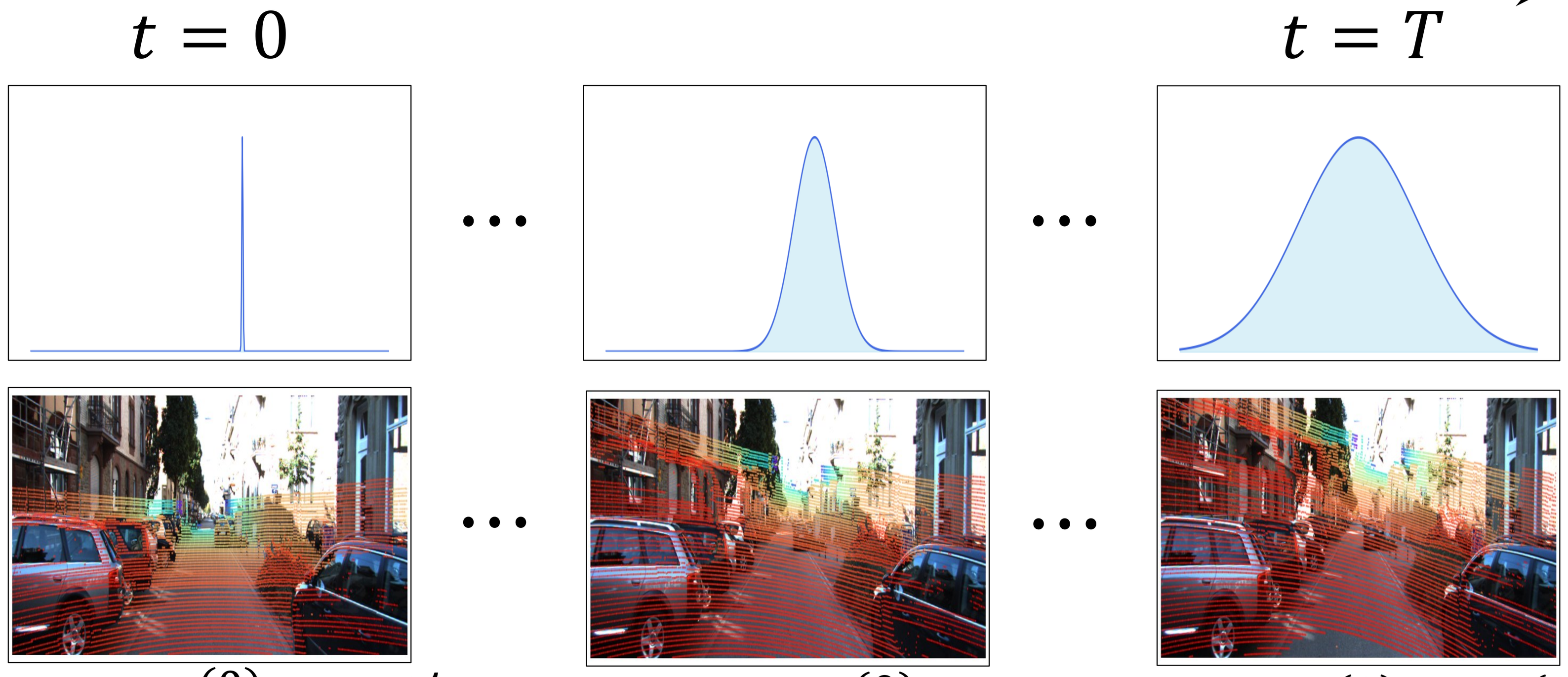
Comparison of Iterative Models

	versatility	accuracy	cost
Naive	Yes	Low	Low
Multi-Range	Yes	High	High
Internal	No	High	Low
Diffusion	Yes	High	Low

Methodology

Noise-Adding: $\boldsymbol{x}_t = \boldsymbol{q}(\boldsymbol{x}_t|\boldsymbol{x}_0,\boldsymbol{\epsilon}), \boldsymbol{\epsilon}\sim\mathcal{N}(0,\boldsymbol{E})$

$t = 0$ … $t = T$



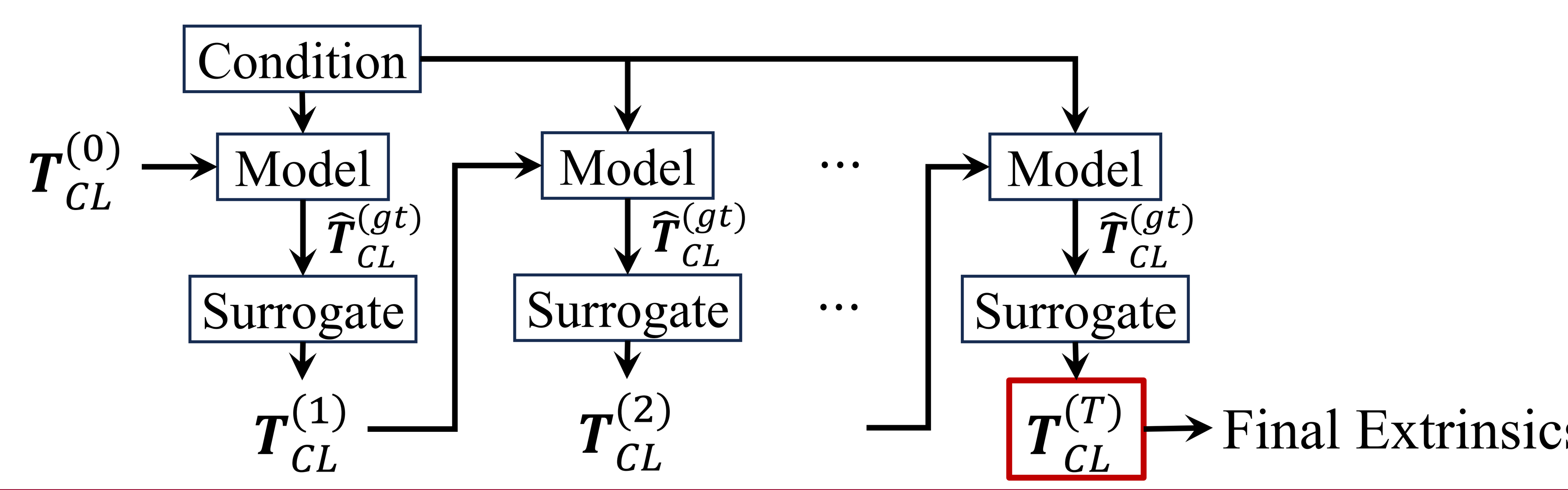
$\mathcal{G}(\boldsymbol{x}_0)\boldsymbol{T}^{(0)}_{CL} = \boldsymbol{T}^{gt}_{CL}$ $\quad$ $\mathcal{G}(\boldsymbol{x}_t)\boldsymbol{T}^{(0)}_{CL}$ $\quad$ $\mathcal{G}(\boldsymbol{x}_T)\boldsymbol{T}^{(0)}_{CL} = \boldsymbol{T}^{(0)}_{CL}$

Denoising: $\boldsymbol{x}_{t-1} = \boldsymbol{q}(\boldsymbol{x}_{t-1}|\boldsymbol{x}_t,\hat{\boldsymbol{x}}_0),\quad \boldsymbol{x}_T = 0$

Condition ($\boldsymbol{C}$): image, point cloud, camera intrinsics

$$\begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \Rightarrow \text{Surrogate:} \begin{cases} \mathcal{G}(\hat{\boldsymbol{x}}_0)\boldsymbol{T}^{(0)}_{CL} = \hat{\boldsymbol{T}}^{(gt)}_{CL} \Rightarrow \hat{\boldsymbol{x}}_0 \\ \boldsymbol{x}_t \sim \mathcal{N}(\sqrt{\bar{\alpha}_t}\hat{\boldsymbol{x}}_0, (1-\bar{\alpha}_t)\boldsymbol{I}) \\ \boldsymbol{x}_{t-1} = \boldsymbol{q}(\boldsymbol{x}_{t-1}|\boldsymbol{x}_t,\hat{\boldsymbol{x}}_0) \\ \boldsymbol{T}^{(i)}_{CL} = \mathcal{G}(\boldsymbol{x}_{T-i})\boldsymbol{T}^{(0)}_{CL} \end{cases}$$

Model: $\hat{\boldsymbol{T}}^{(gt)}_{CL} = \mathcal{G}\left(D_\theta\left(C, \boldsymbol{T}^{(i)}_{CL}\right)\right)\boldsymbol{T}^{(i)}_{CL}$



Results

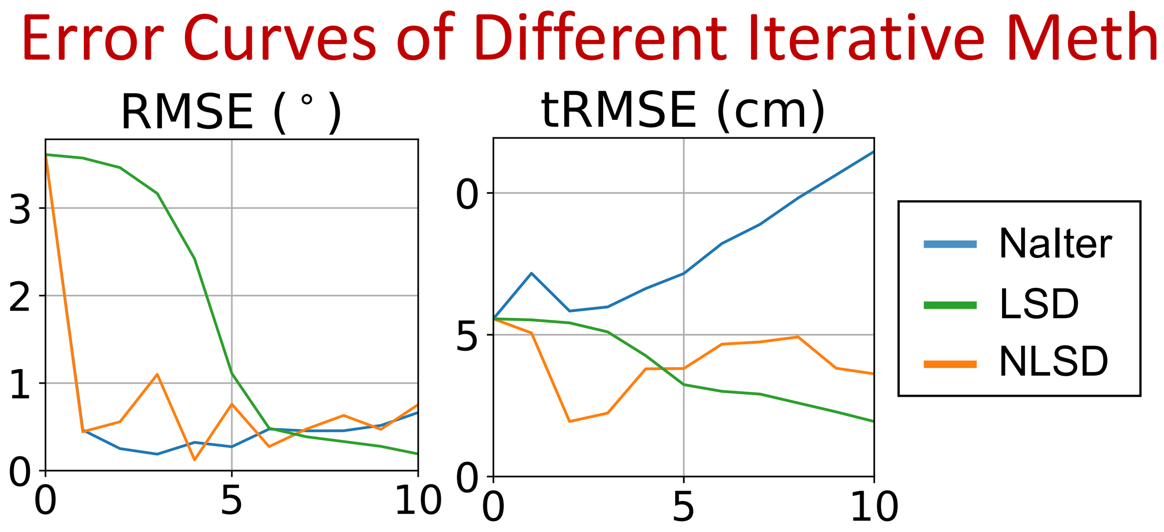
Robustness: Models × Iterative Methods

Method	3°3cm↑	5°5cm↑	ρ%↑
CalibNet (Single)	23.19%	49.37%	N/A
RGGNet (Single)	22.04%	43.53%	N/A
LCCNet (Single)	23.88%	48.47%	N/A
LCCRAFT (Single)	26.38%	47.33%	N/A
CalibNet + NaIter	12.50%	32.75%	2.98%
RGGNet + NaIter	19.65%	39.90%	8.55%
LCCNet + NaIter	13.28%	34.58%	4.74%
LCCRAFT + NaIter	10.39%	27.45%	4.75%
CalibNet + NLSD	23.46%	47.96%	7.66%
RGGNet + NLSD	20.67%	43.04%	6.19%
LCCNet + NLSD	26.15%	48.94%	7.15%
LCCRAFT + NLSD	26.29%	46.74%	7.16%
CalibNet + LSD	**24.39%**	**49.52%**	**38.62%**
RGGNet + LSD	**22.24%**	**44.09%**	**38.86%**
LCCNet + LSD	**26.27%**	**50.14%**	**45.54%**
LCCRAFT + LSD	**27.90%**	**49.96%**	**47.61%**

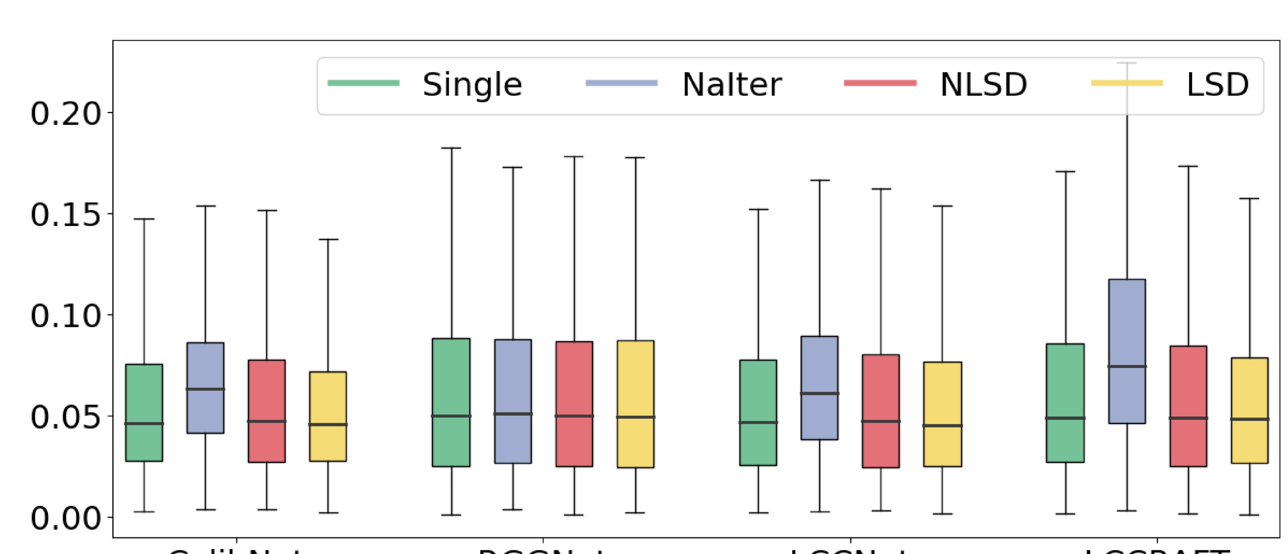
Inference Speed (ms/batch)

Method	Single↓	NaIter↓	NLSD↓	LSD↓
CalibNet	40.67	198.67	226.01	235.11
RGGNet	52.53	321.16	348.10	356.91
LCCNet	65.36	448.07	475.99	483.28
LCCRAFT	381.76	3002.66	3024.40	3097.26

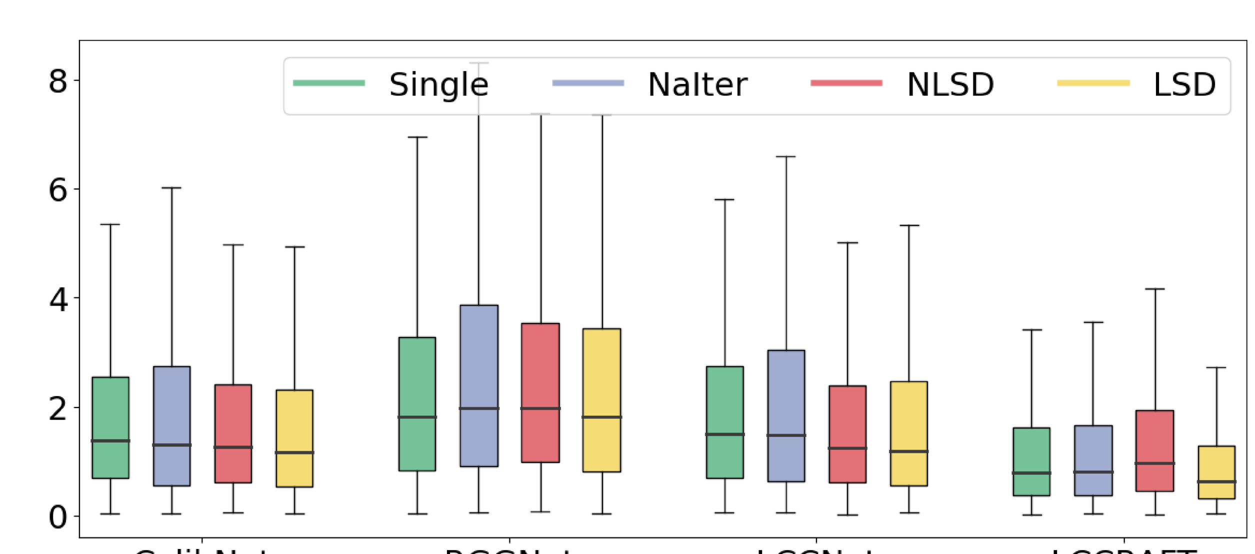
Error Curves of Different Iterative Methods

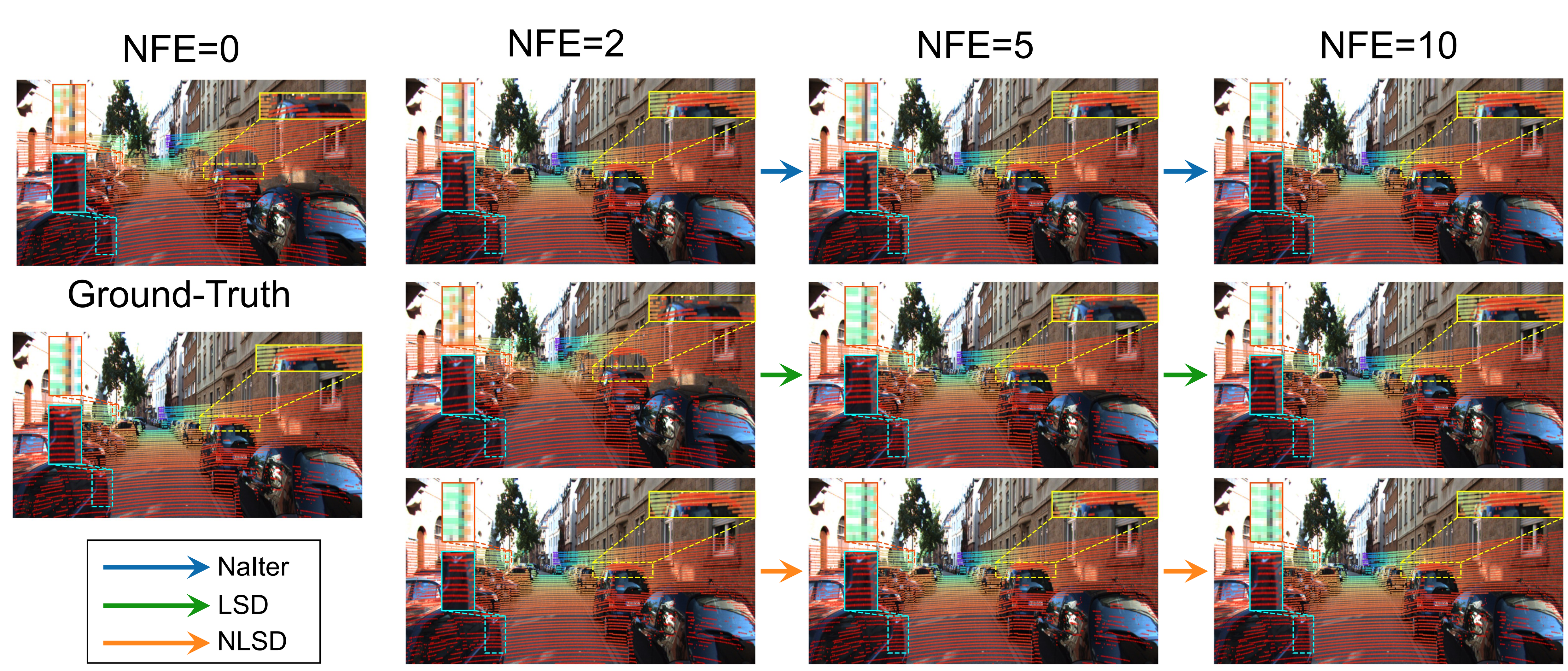


RMSE: Models × Iterative Methods



tMSE: Models × Iterative Methods





Coclusion

We proposed a Linear Surrogate Diffusion (LSD) model for denoiser-agnostic iterative camera-LiDAR calibration. Experiments on the KITTI dataset illustrate that LSD outperforms other single-model iterative methods in terms of accuracy, robustness and stability.