

Learning Correspondence Uncertainty via Differentiable Nonlinear Least Squares



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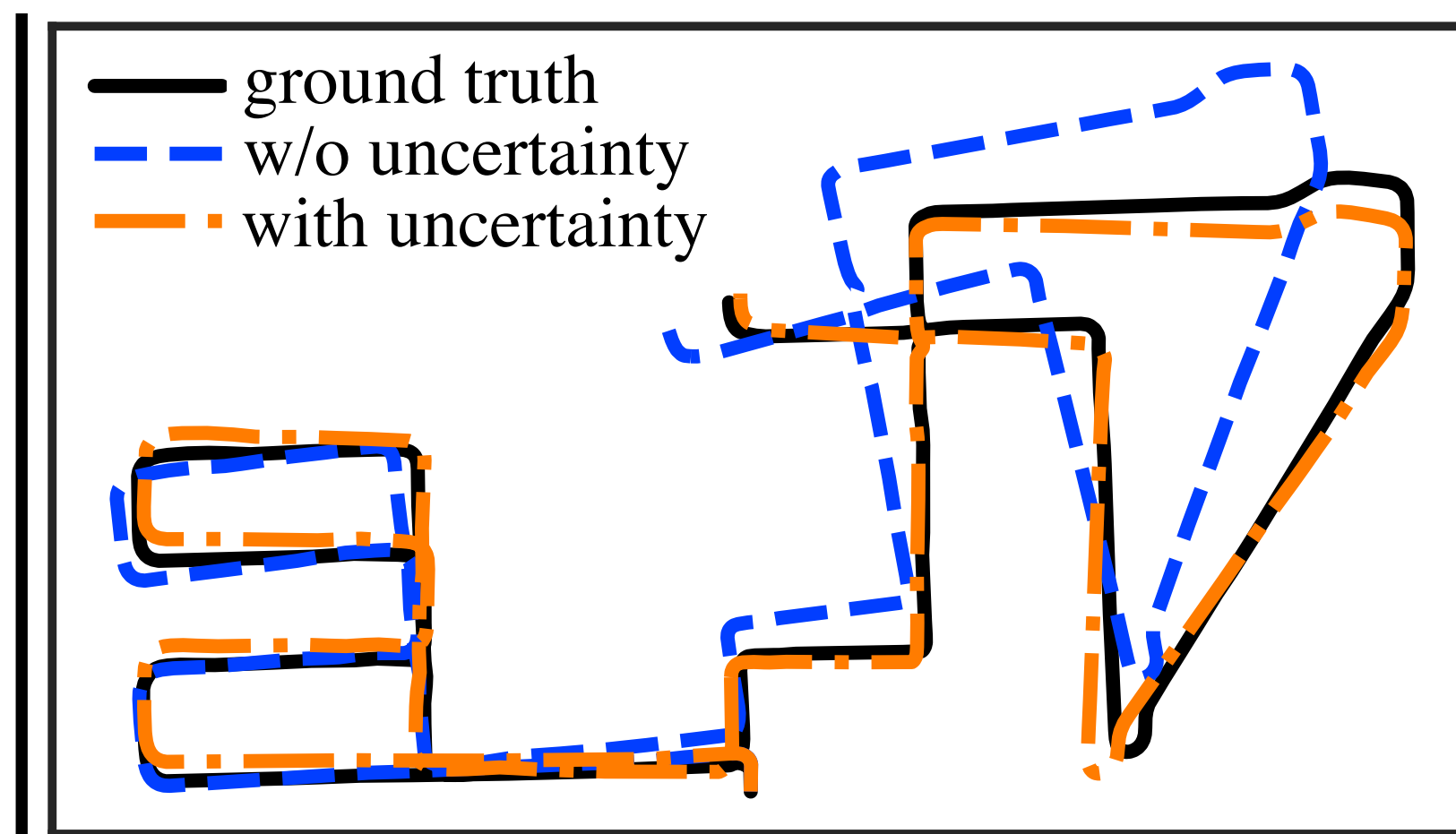
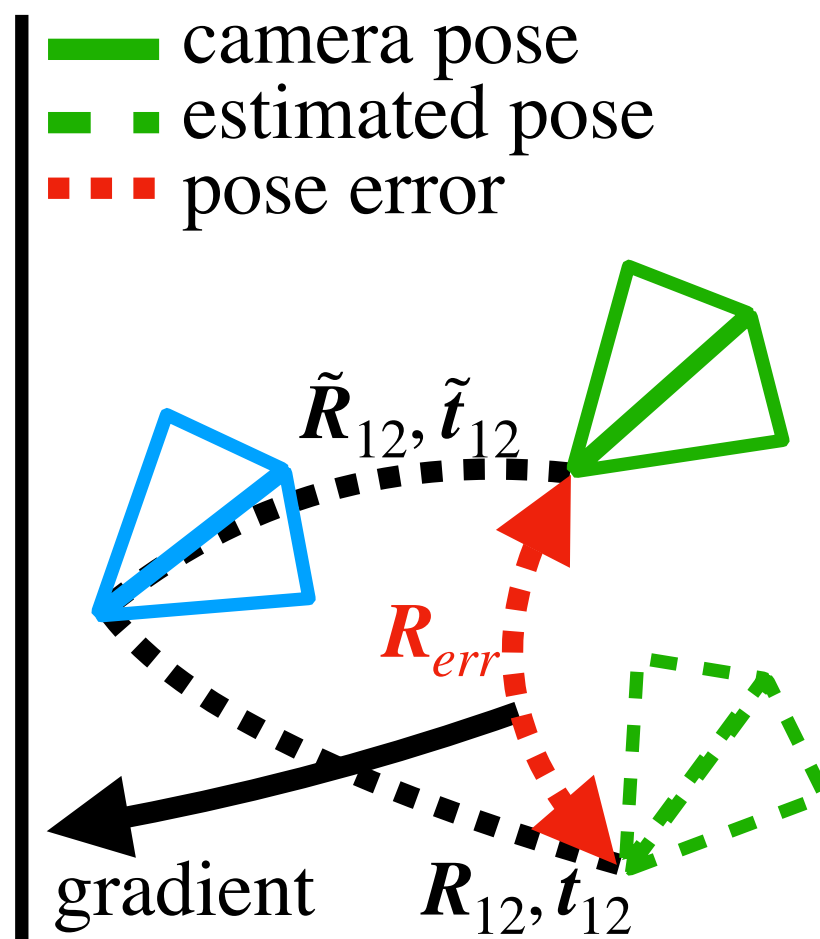
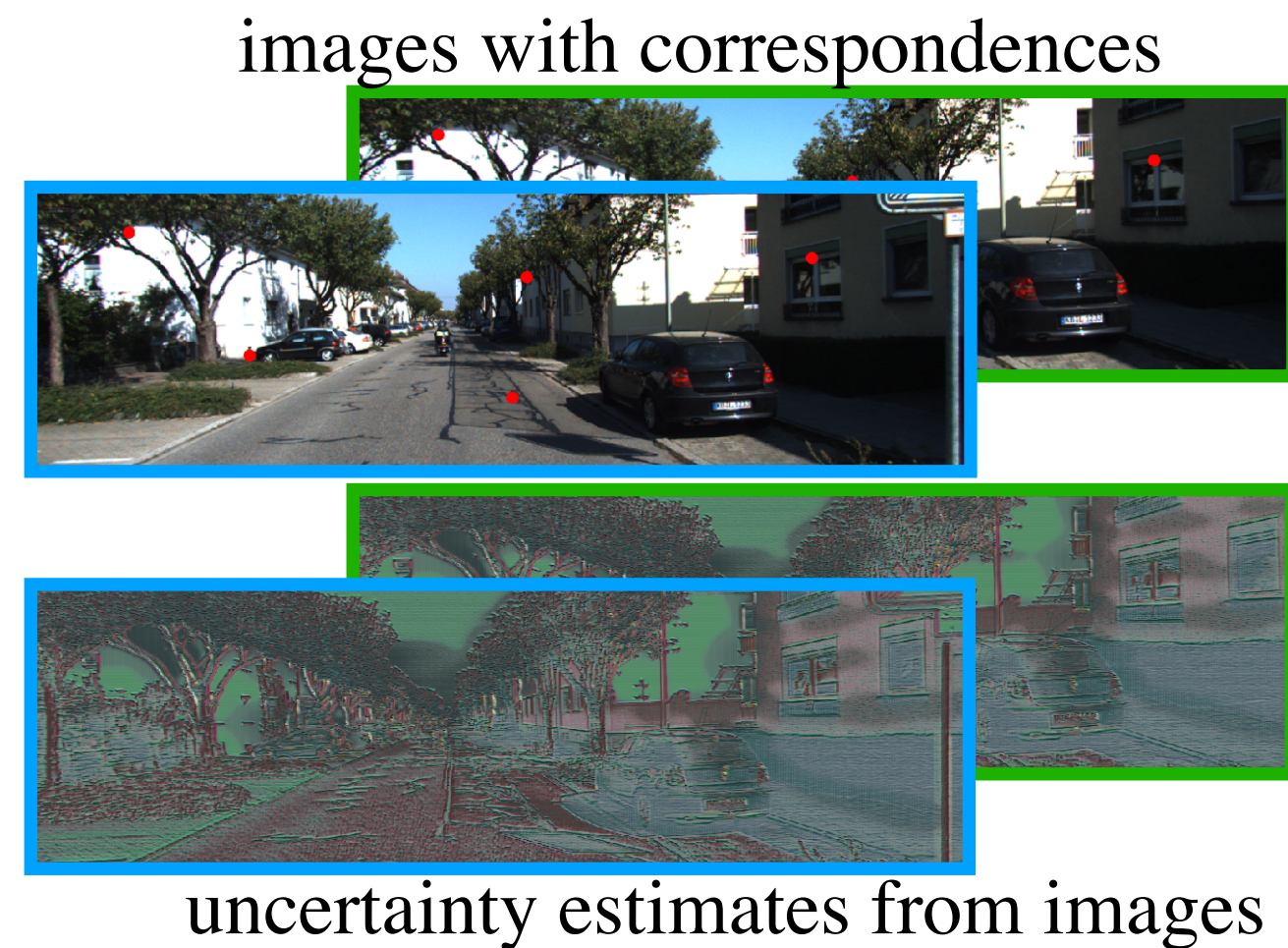
Daniel Cremers^{1,2,3}

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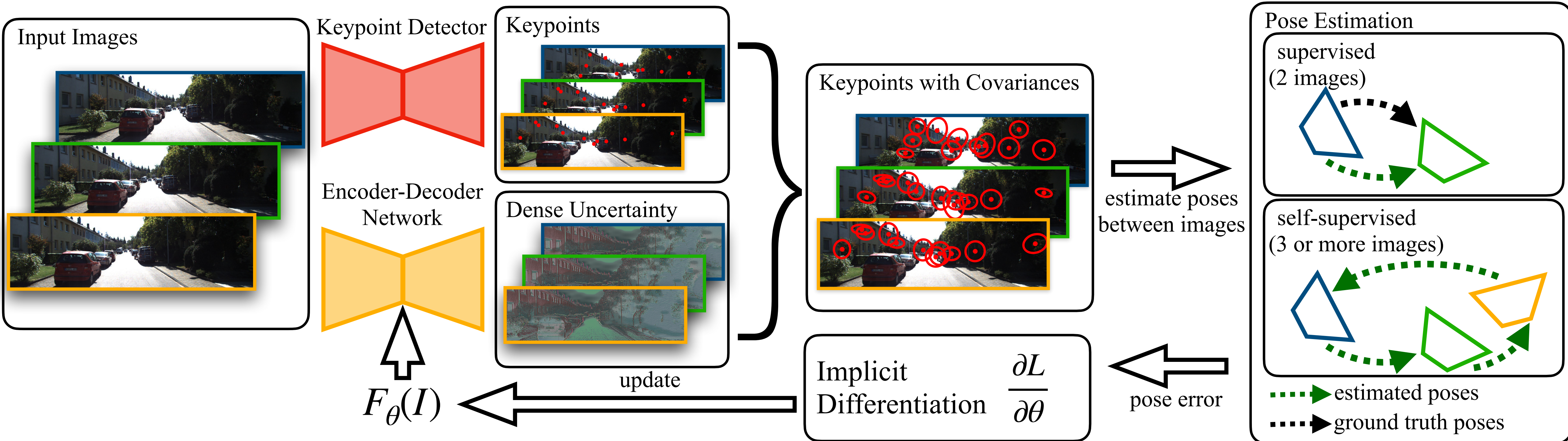
²MCML

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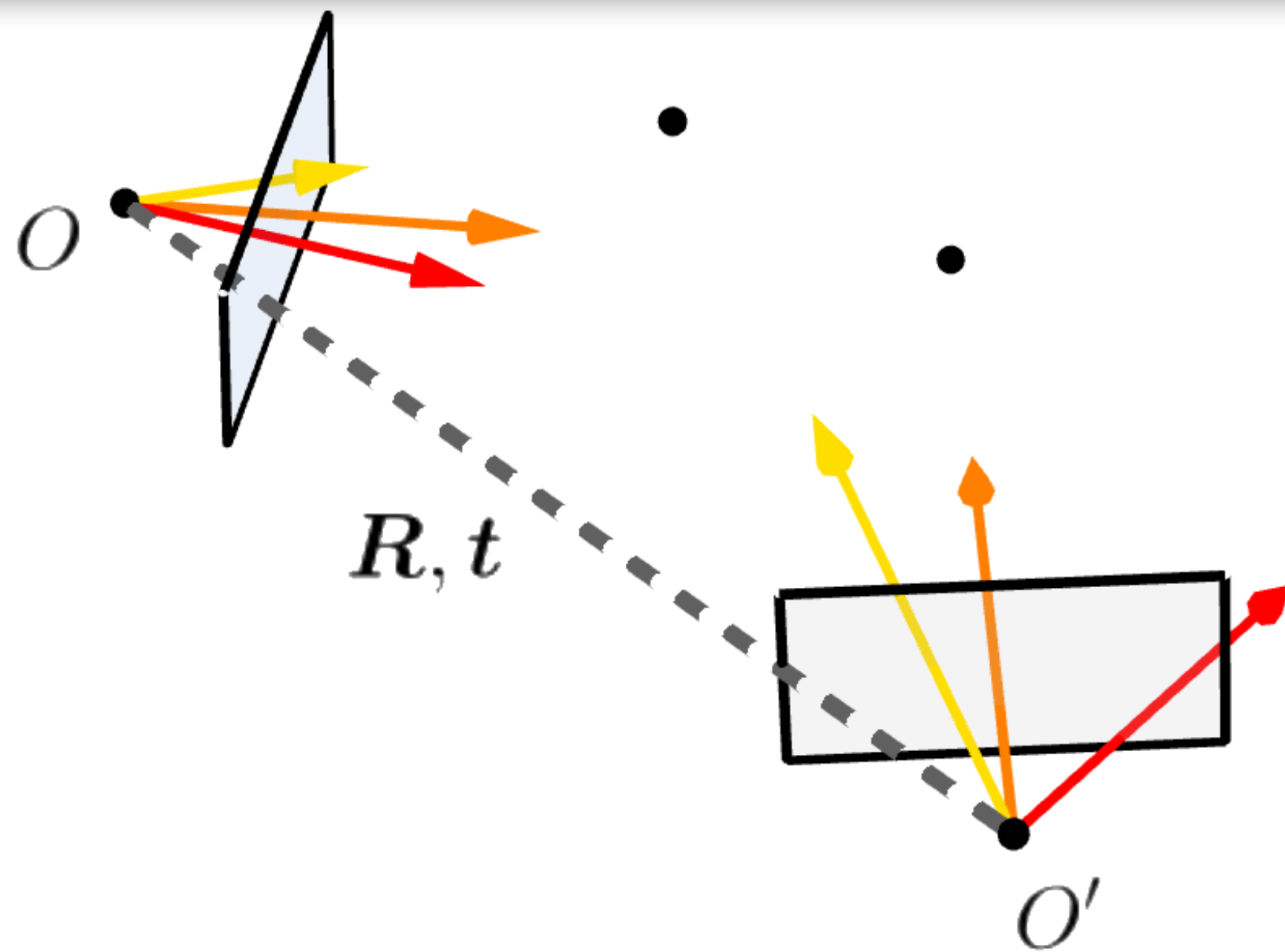
⁴MIT



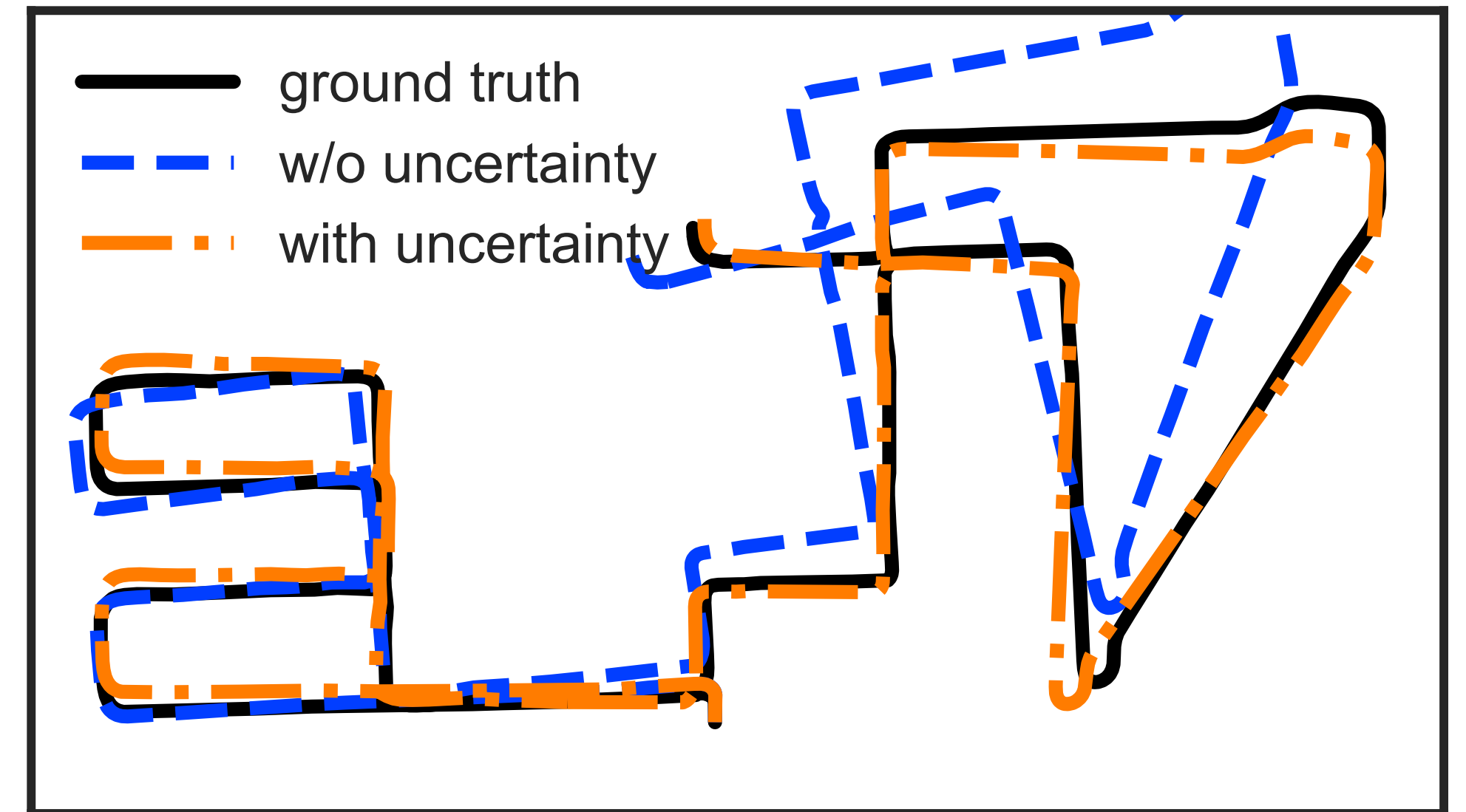
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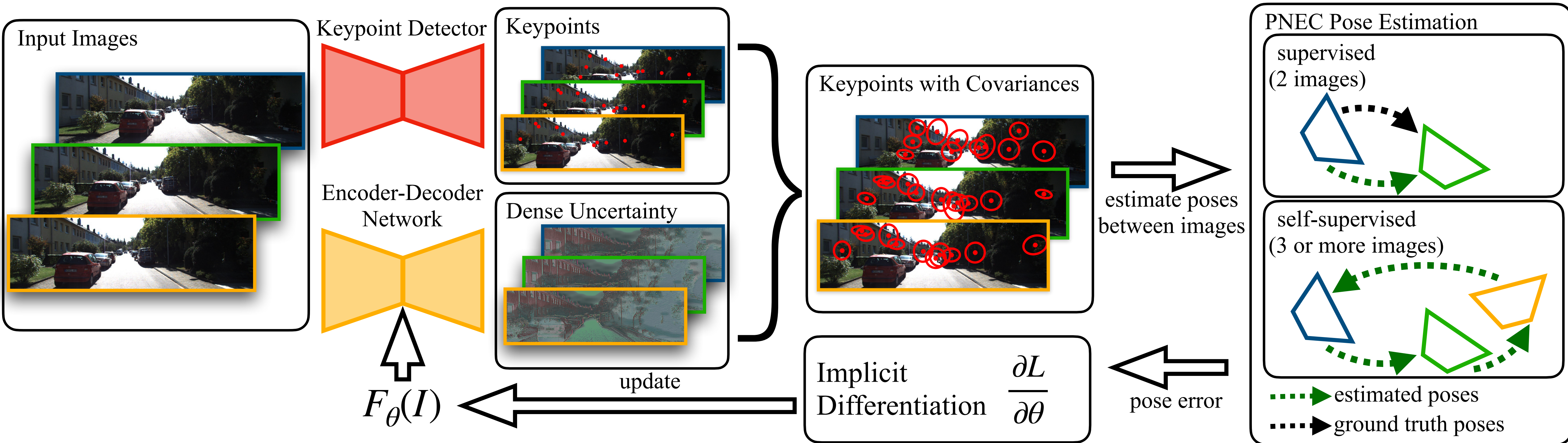
Why use Uncertainty in Visual Odometry?



Visual Odometry



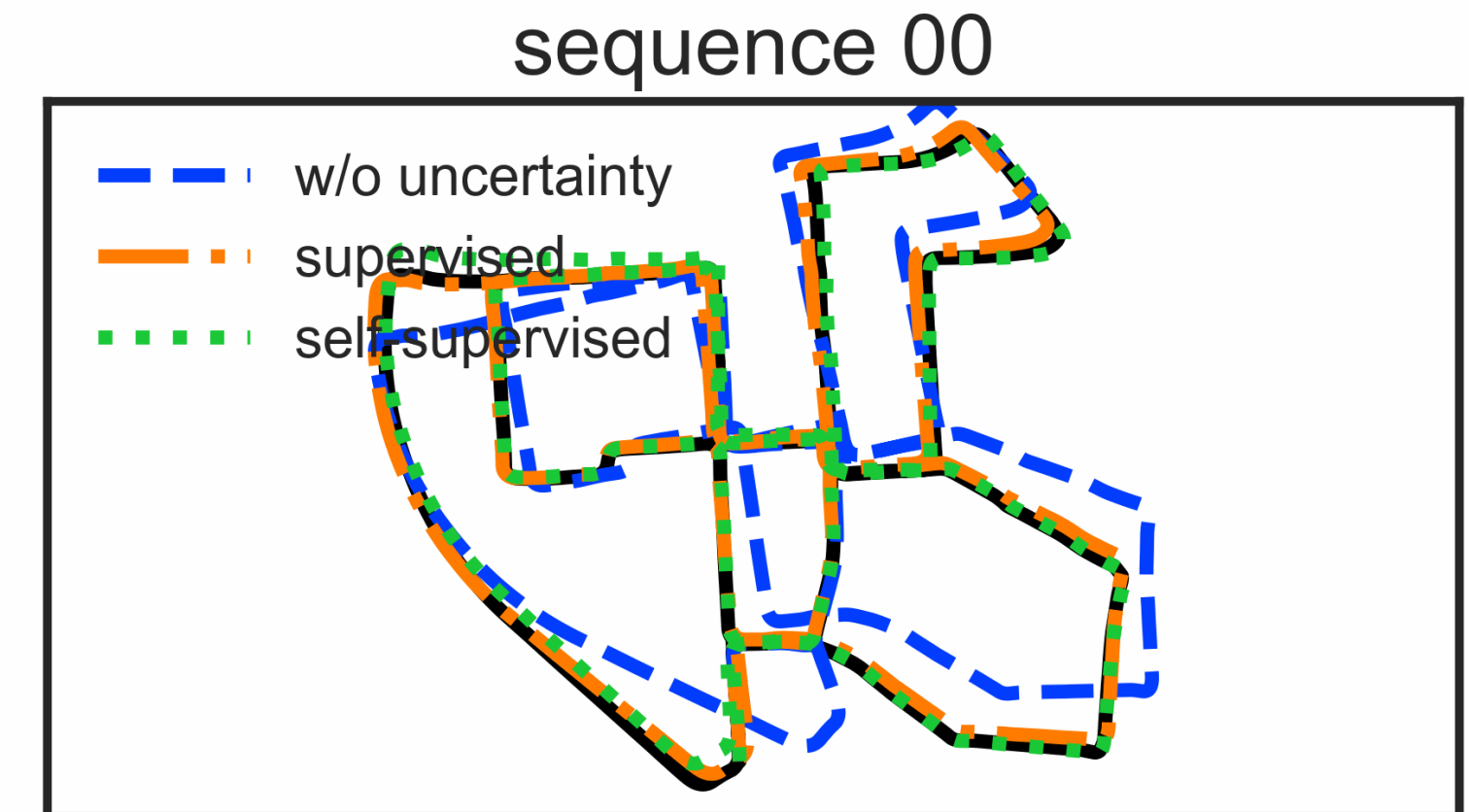
Training on Real World Data



Architecture: The formulation of our framework allows us to train our network in a supervised and with more than 3 images in a self-supervised manner.

Evaluation on Real World Data

	NISTÉR-5PT [50]			NEC [33]			NEC-LS			WEIGHTED NEC-LS			OURS SUPERVISED			OURS SELF- SUPERVISED		
Seq.	RPE ₁	RPE _n	e _t	RPE ₁	RPE _n	e _t	RPE ₁	RPE _n	e _t	RPE ₁	RPE _n	e _t	RPE ₁	RPE _n	e _t	RPE ₁	RPE _n	e _t
08	0.195	17.020	4.24	0.081	8.284	3.66	0.056	7.004	2.50	0.054	6.059	2.50	0.050	4.067	2.46	<u>0.050</u>	<u>4.118</u>	2.46
09	0.142	5.754	1.74	0.053	1.646	1.43	0.052	1.553	0.71	0.051	1.354	0.70	<u>0.049</u>	<u>1.317</u>	0.71	0.049	1.278	<u>0.70</u>
10	0.295	16.678	6.57	0.167	9.264	4.43	0.064	4.787	1.79	0.063	4.389	1.76	<u>0.063</u>	3.513	1.64	0.065	<u>3.821</u>	<u>1.65</u>
train	0.249	11.506	4.13	0.141	10.127	2.97	0.082	6.910	1.72	0.081	6.410	1.72	<u>0.077</u>	2.378	1.69	0.077	<u>2.505</u>	<u>1.69</u>
test	0.200	14.349	4.07	0.089	6.917	3.28	0.056	5.353	1.96	0.055	4.676	1.95	0.052	3.333	<u>1.91</u>	<u>0.053</u>	<u>3.408</u>	1.91



Evaluation on the KITTI odometry dataset for SuperPoint + SuperGlue keypoints. As there are no uncertainty estimates for SuperPoint, we use SuperGlue confidence as a stand-in for the WEIGHTED NEC-LS

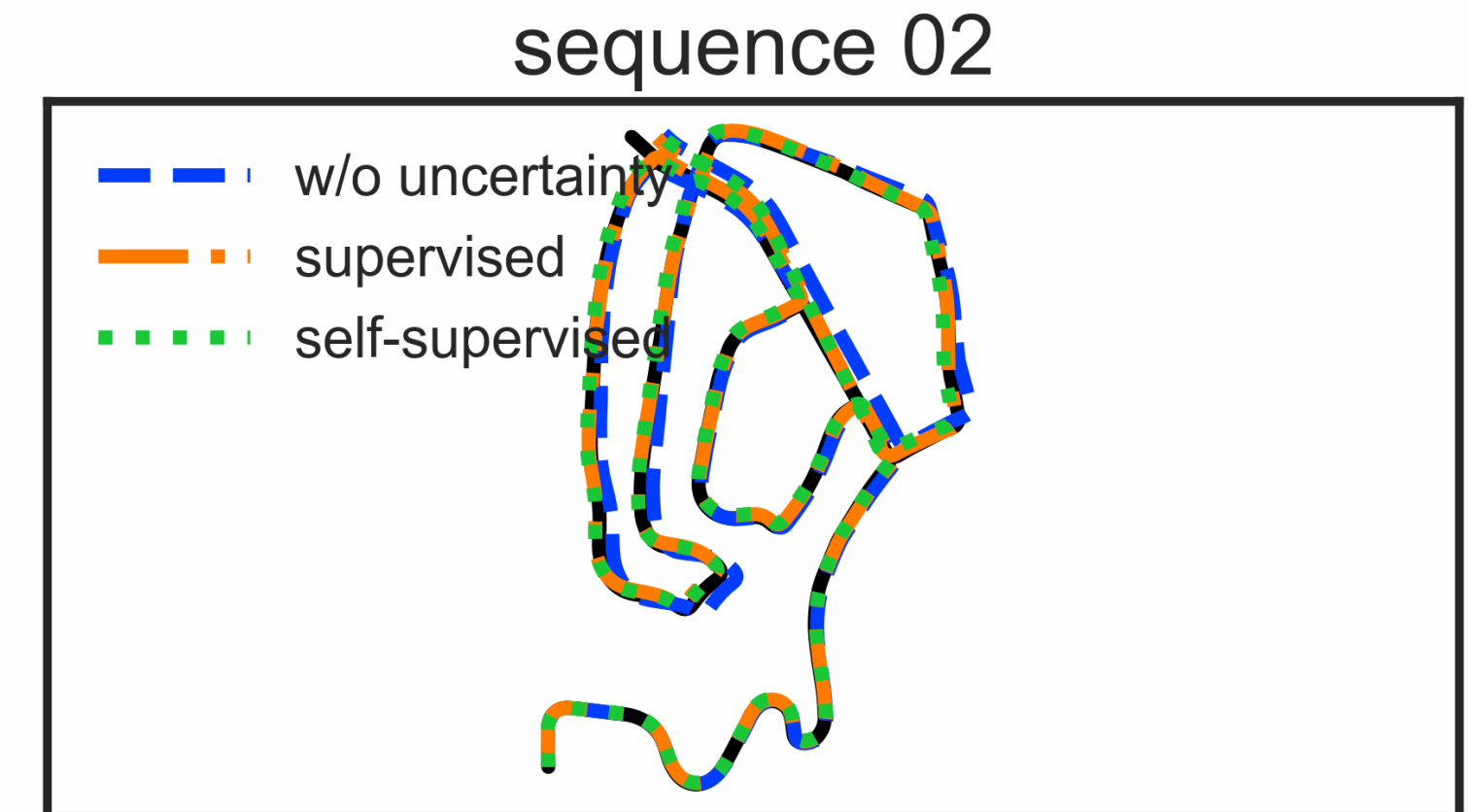
[33] Laurent Kneip and Simon Lynen. Direct optimization of frame-to-frame rotation. *ICCV*, 2013

[50] D. Nister. An efficient solution to the five-point relative pose problem. *CVPR*, 2003

Results: Our estimated covariances lead to lower rotational and translational error for a supervised and self-supervised training. They outperform non-probabilistic and probabilistic pose estimates.

Evaluation on Real World Data

Seq.	NISTÉR-5PT [50]			NEC [33]			NEC-LS			KLT-PNEC [48]			OURS SUPERVISED			OURS SELF-SUPERVISED		
	RPE ₁	RPE _n	e_t	RPE ₁	RPE _n	e_t	RPE ₁	RPE _n	e_t	RPE ₁	RPE _n	e_t	RPE ₁	RPE _n	e_t	RPE ₁	RPE _n	e_t
08	0.126	6.929	3.44	0.088	3.902	8.91	0.053	2.908	2.49	0.054	2.524	2.42	<u>0.048</u>	<u>2.373</u>	2.36	0.047	1.706	<u>2.36</u>
09	0.090	2.544	1.28	0.054	2.027	6.76	0.052	2.307	0.74	0.046	1.003	0.69	<u>0.043</u>	1.244	0.64	0.042	<u>1.141</u>	<u>0.64</u>
10	0.188	11.554	4.43	0.119	8.302	8.53	0.066	4.576	1.78	0.063	4.480	1.71	<u>0.058</u>	<u>3.789</u>	1.58	0.056	3.623	<u>1.60</u>
train	0.204	9.677	3.19	0.173	8.301	8.59	0.103	3.955	1.73	0.104	4.213	1.66	0.094	<u>2.782</u>	1.60	<u>0.096</u>	2.737	<u>1.61</u>
test	0.129	6.722	3.11	0.085	4.237	8.34	0.055	3.060	1.96	0.054	2.514	1.90	<u>0.048</u>	<u>2.359</u>	1.82	0.048	1.910	<u>1.83</u>



Evaluation on the KITTI odometry dataset for Kanade-Lucas-Tomasi tracking keypoints.

[33] Laurent Kneip and Simon Lymen. Direct optimization of frame-to-frame rotation. *ICCV*, 2013

[48] D Muhle, L Koestler, N Demmel, F Bernard, and D Cremers. The probabilistic normal epipolar constraint for frame-to-frame rotation optimization under uncertain feature positions. *CVPR*, 2022

[50] D. Nister. An efficient solution to the five-point relative pose problem. *CVPR*, 2003

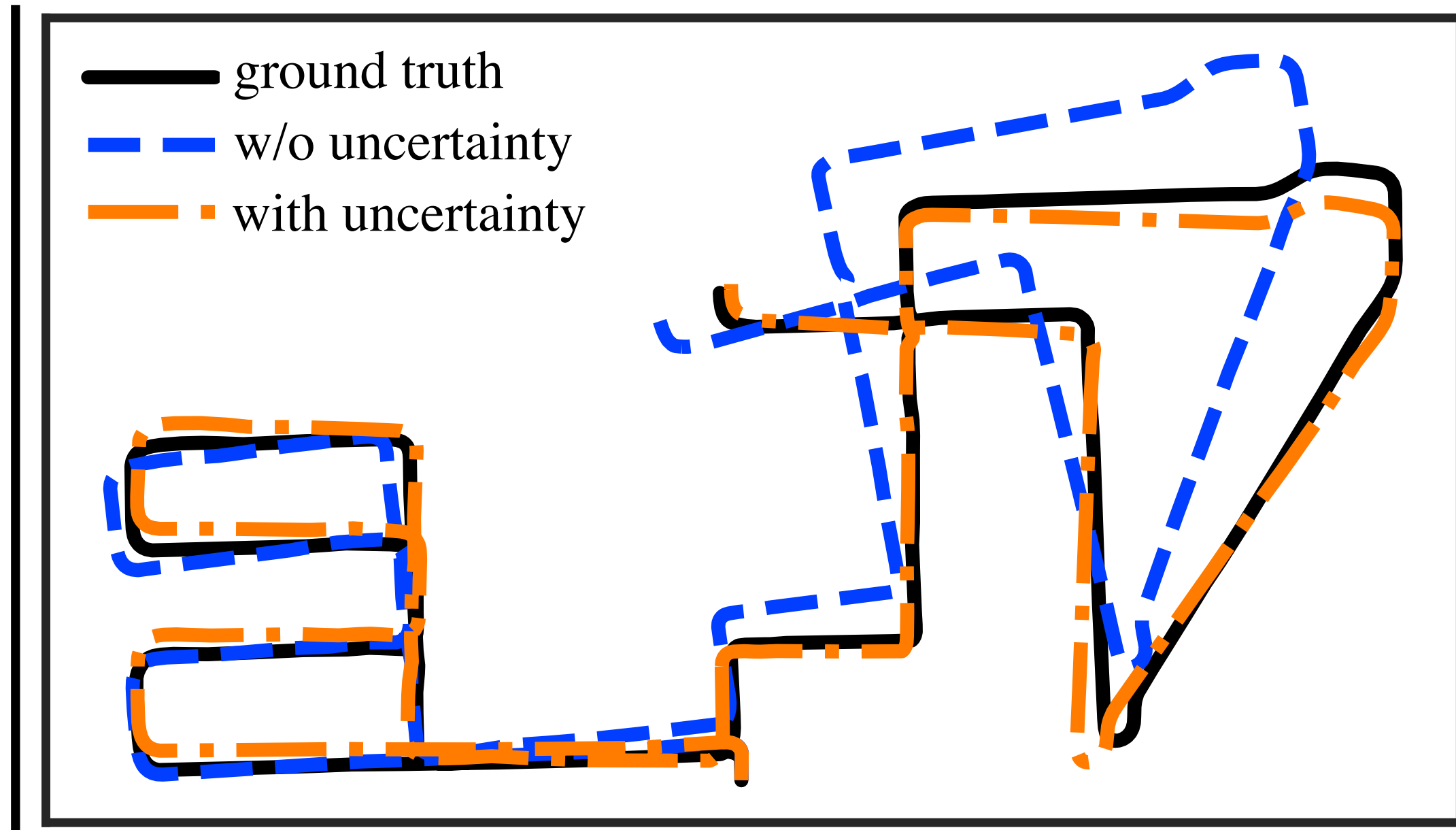
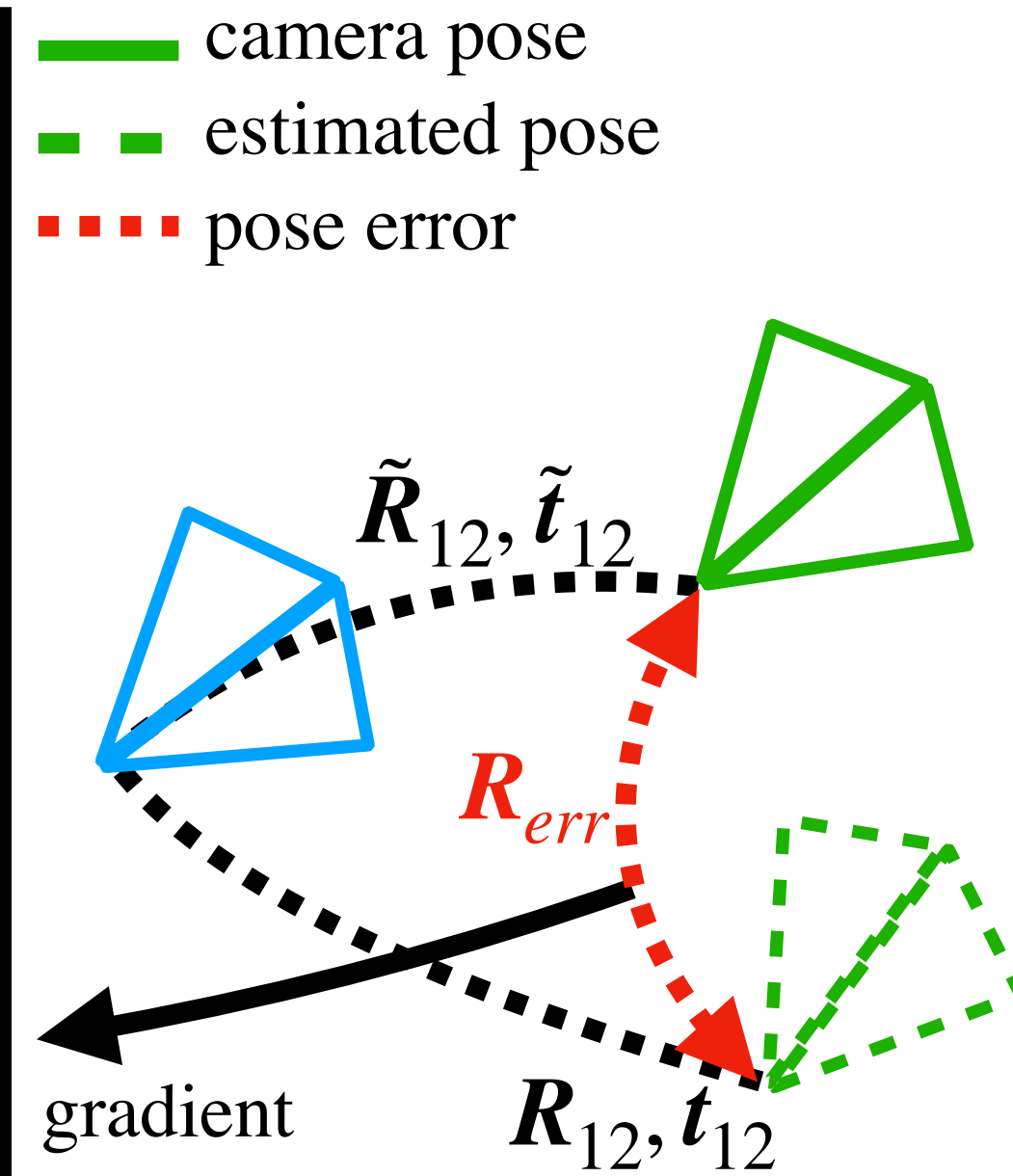
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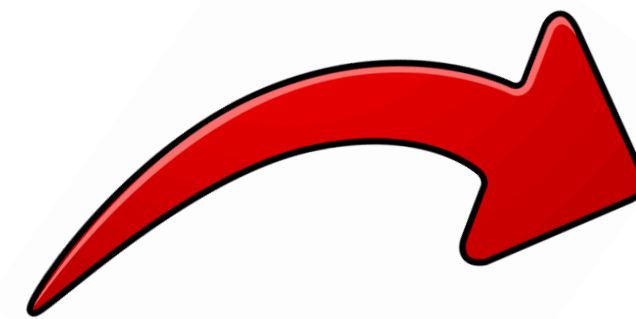
images with correspondences



uncertainty estimates from images



Code
Paper
Data



https://dominikmuhle.github.io/dnls_covs/