Robotics and
Visual Intelligence Lab

Digging Into Self-Supervised Monocular Depth Estimation (Monodepth2)

Clement Godard[1] Oisin Mac Aodha[2] Michael Firman[3] Gabriel Brostow[3,1]
[1]UCL [2]Caltech [3]Niantic

ICCV 2019

Gyeongsu Cho @UNIST

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Monocular Depth Estimation

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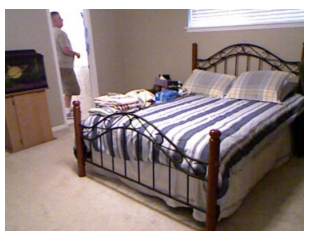
Supervised Monocular Training

Self-supervised Monocular Training

Introduction

Supervised Monocular Training [1]



RGB

→ Model →

Depth prediction

Self-supervised Monocular Training

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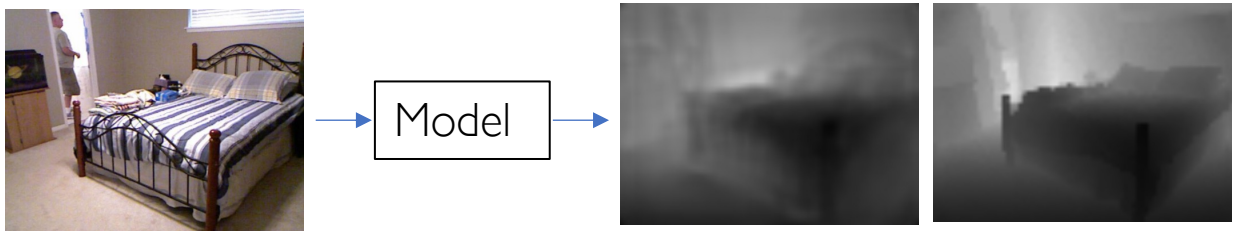
Supervised Monocular Training [1]



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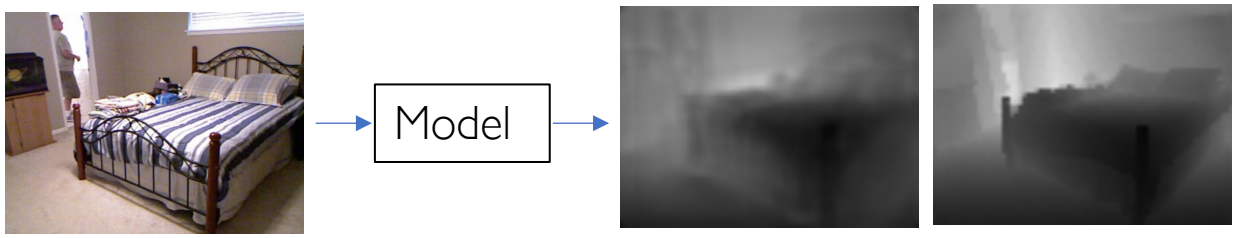

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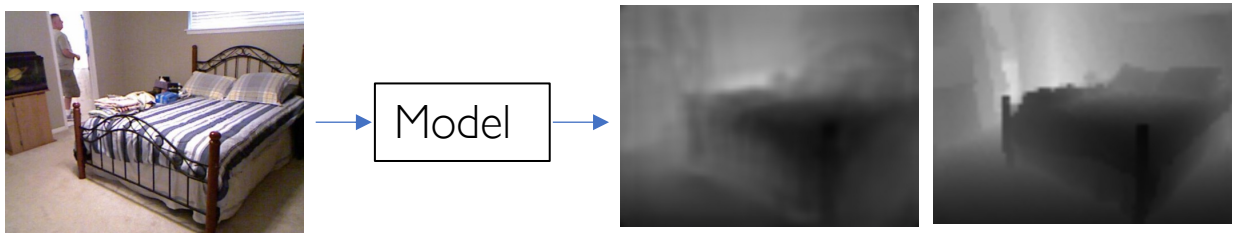

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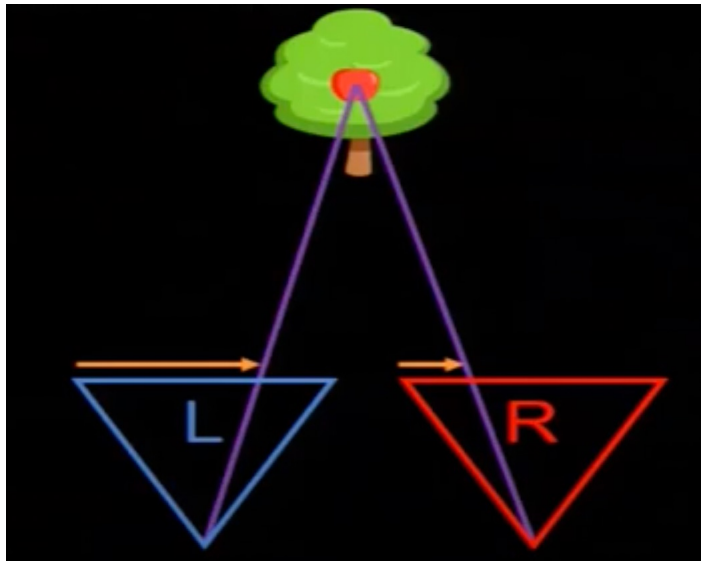

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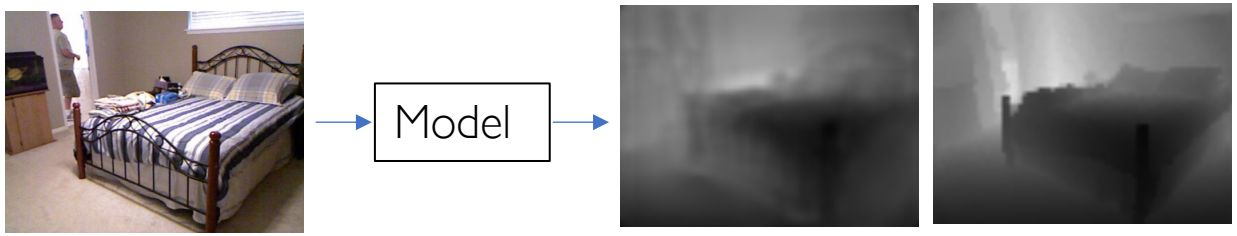
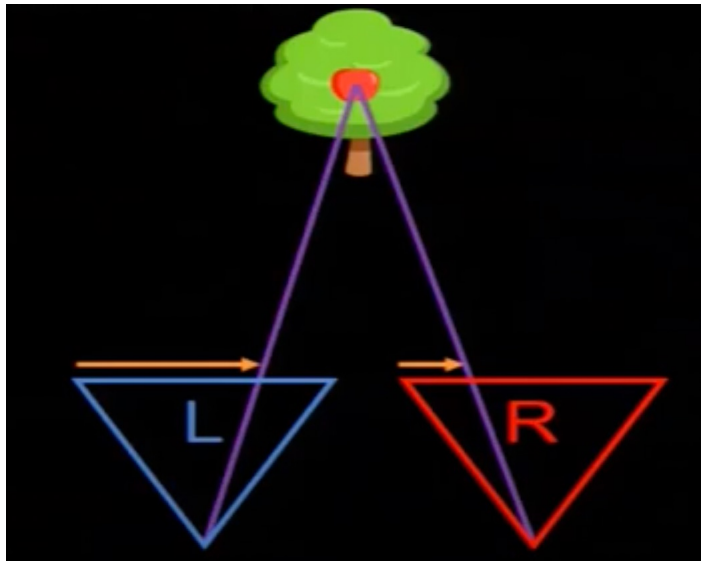
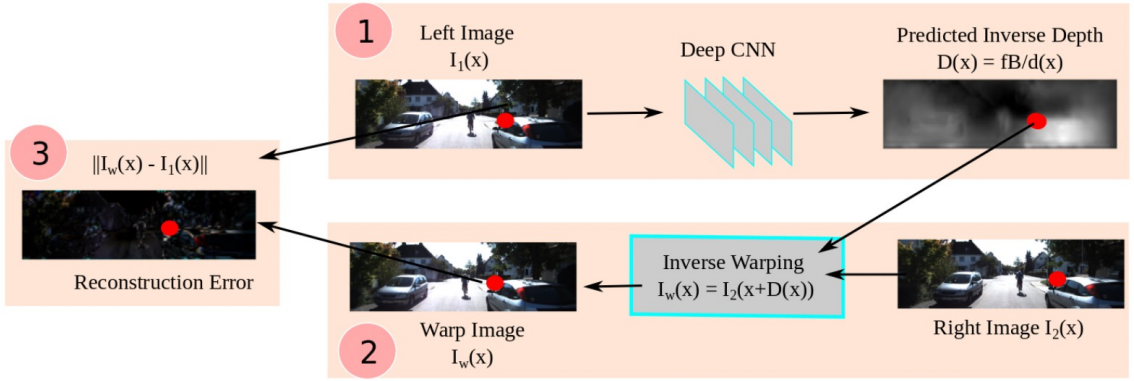


RGB Depth prediction GT

Self-supervised Monocular Training [2]





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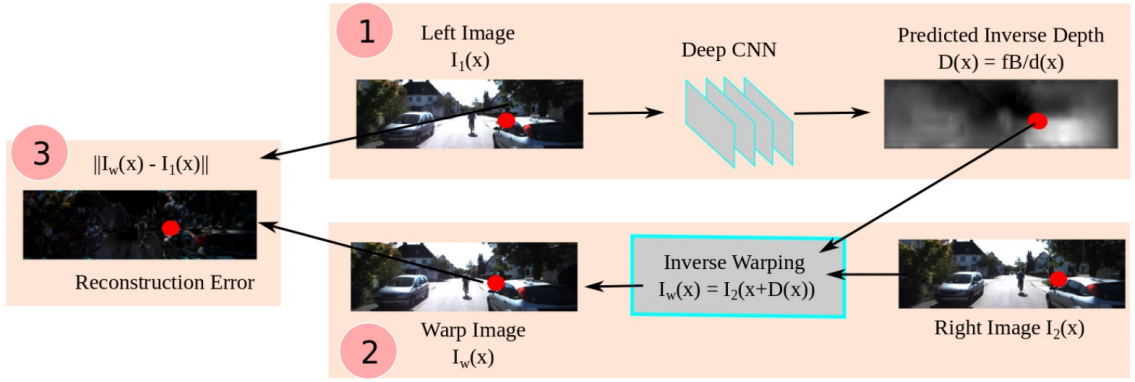
Introduction

Stereo pairs [2]



Monocular videos

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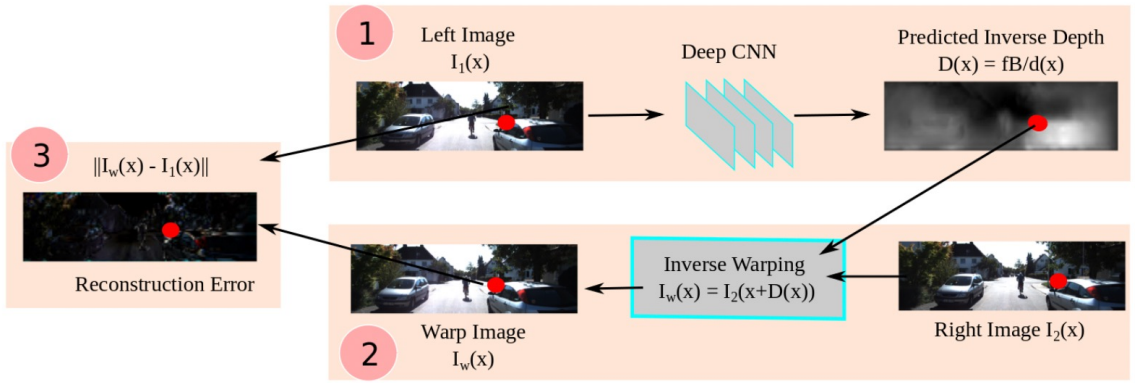
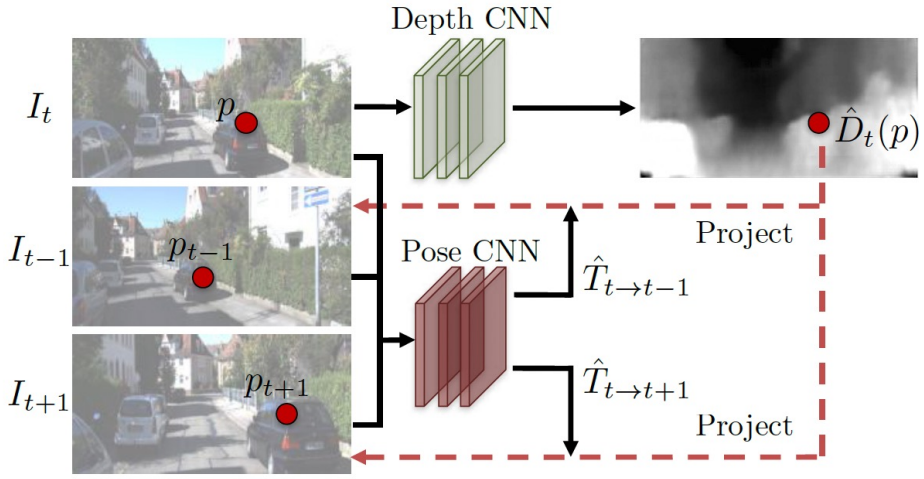


Monocular videos [3]



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[3] Zhou, et al, Unsupervised Learning of Depth and Ego-Motion from Video, In CVPR, 2017

Introduction

Contribution

1. A **novel appearance matching loss** to address the problem of **occluded pixels** that occur when using monocular supervision

2. A novel and simple **auto-masking approach** to ignore pixels where no relative camera motion is observed in monocular training

3. A **multi-scale appearance matching loss** that performs all image sampling at the input resolution, leading to a reduction in depth artifacts

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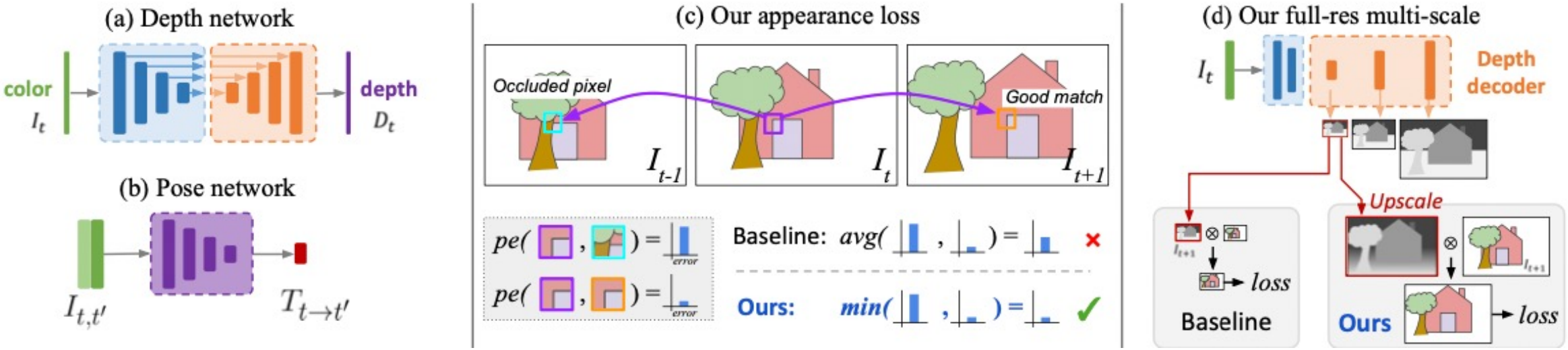
Method

- Overview

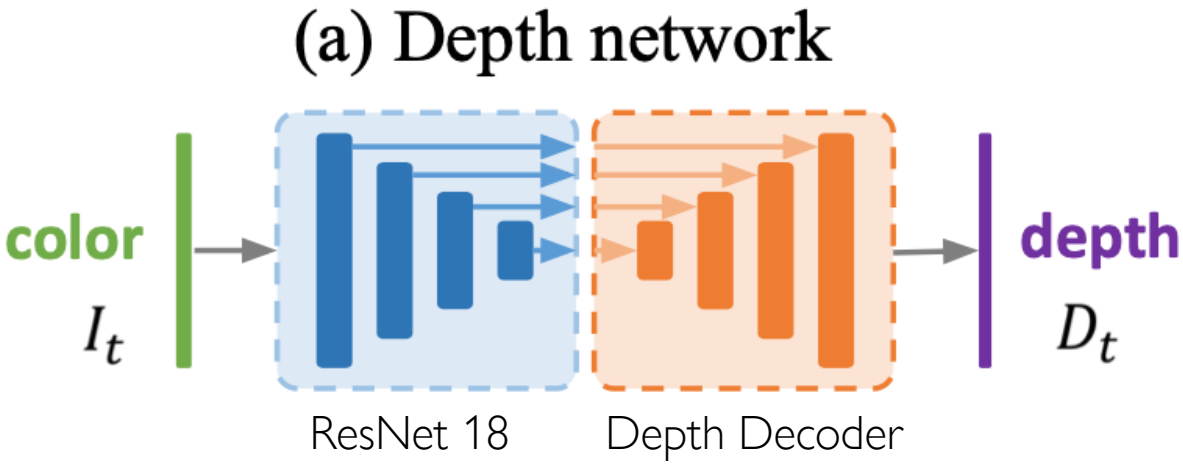


Method

- Network

Method

- Network



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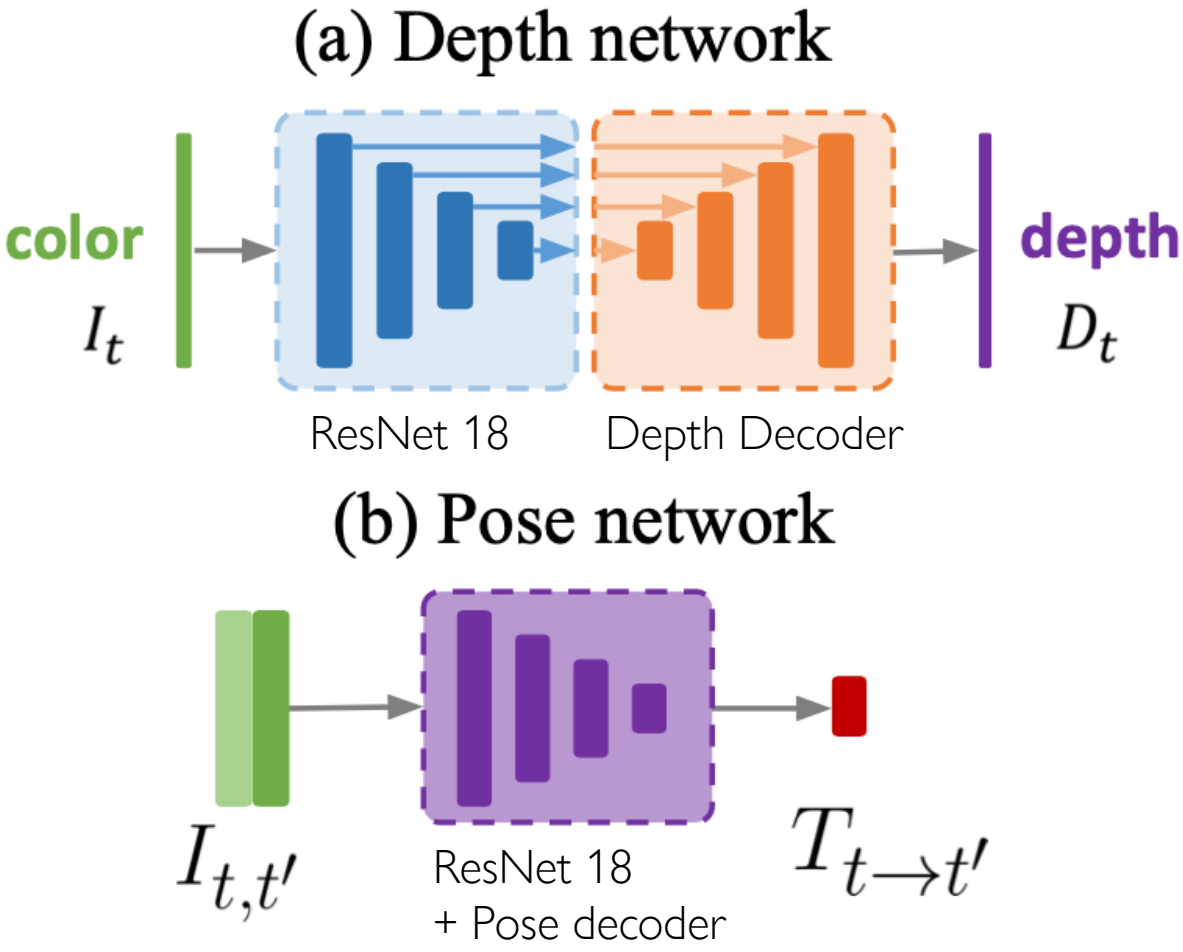

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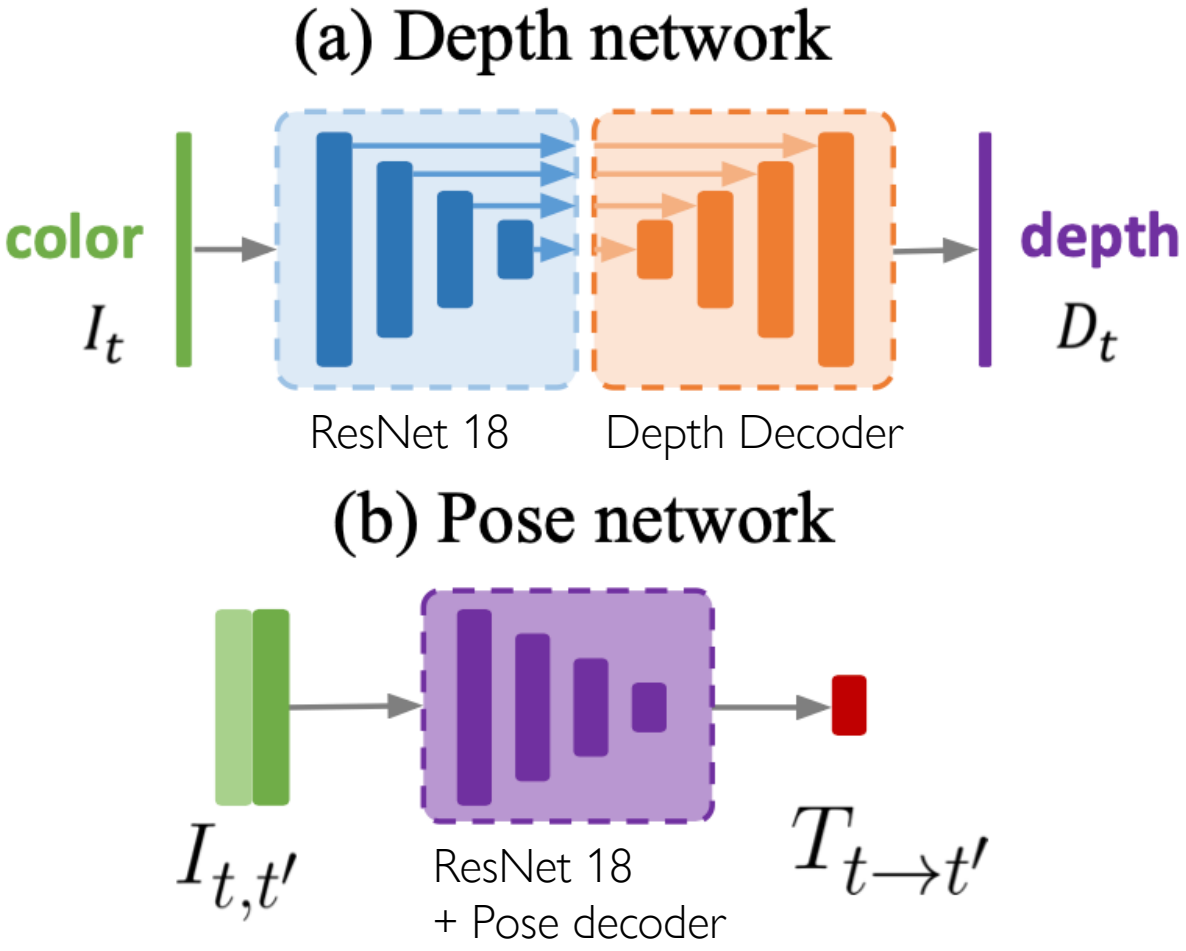


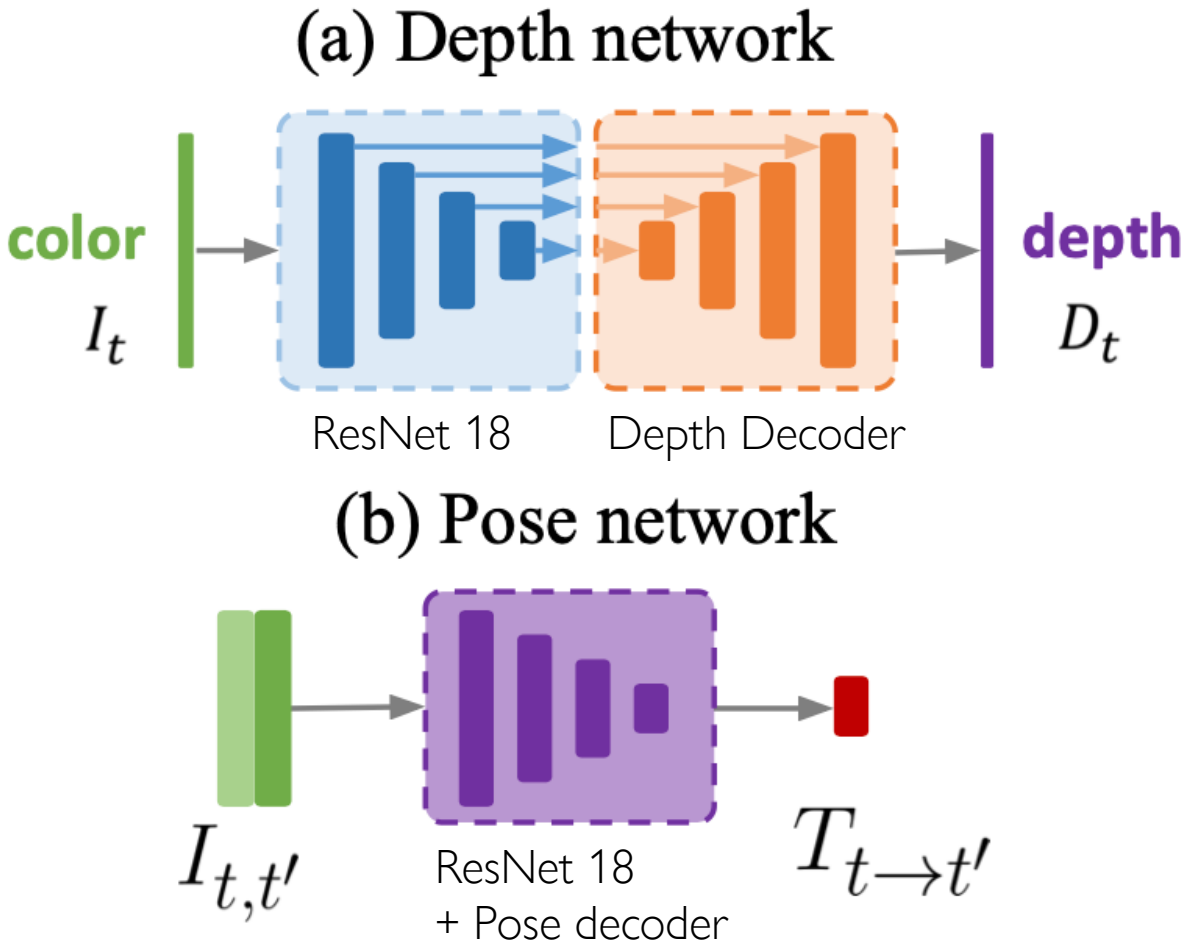
- Loss function

$$L_p = \sum_{t'} pe(I_t, I_{t'\to t}),$$

$$I_{t'\to t} = I_{t'}\left\langle proj(D_t, T_{t\to t'}, K)\right\rangle$$

Method

- Network



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Method

- Projection & Warp

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p_{t'} \sim K T_{t\to t'} D_t(p_t) K^{-1} p_t
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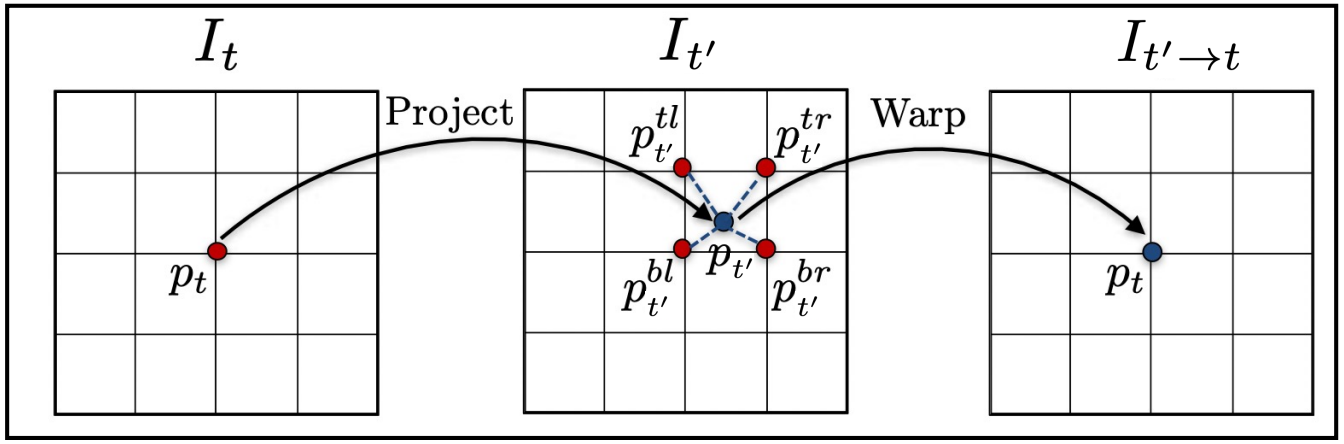
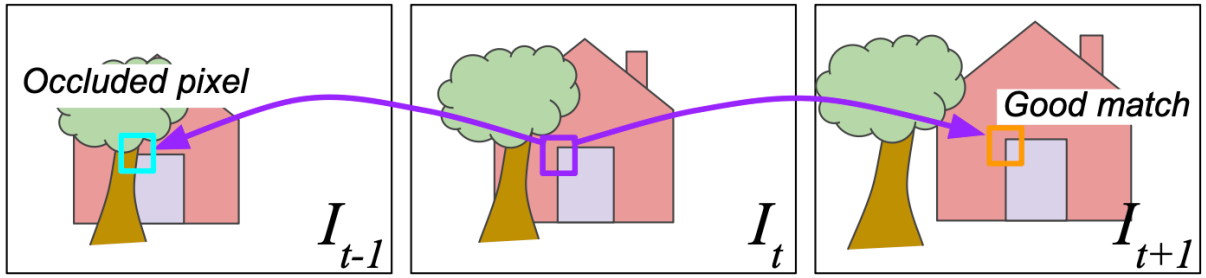


Illustration of the differentiable image warping process.
For each point p_t in the target view, we first project it onto the source view based on the predicted depth and camera pose, and then use **bilinear interpolation** to obtain the value of the warped image $I_{t'}$ at location p_t

Method

1. Per-Pixel Minimum Reprojection Loss



$pe($, $) =$ error

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Baseline: $avg($, $) =$ ✗

Ours: $min($, $) =$ ✓

Method

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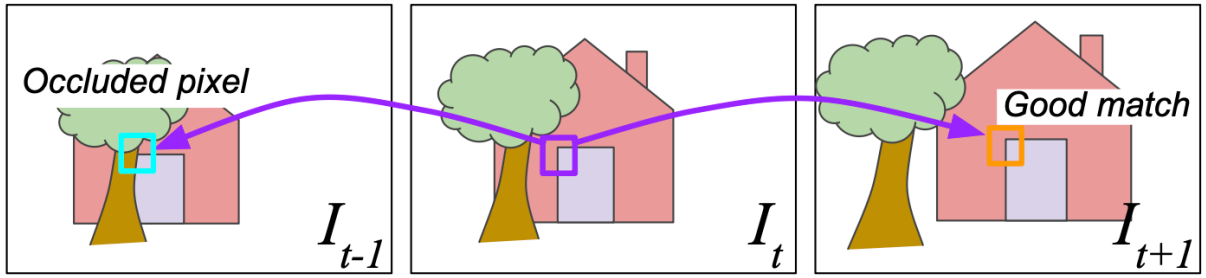

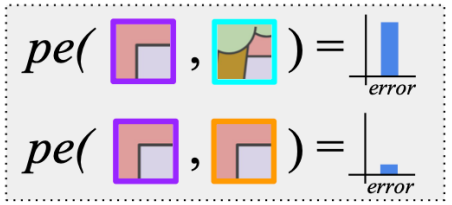

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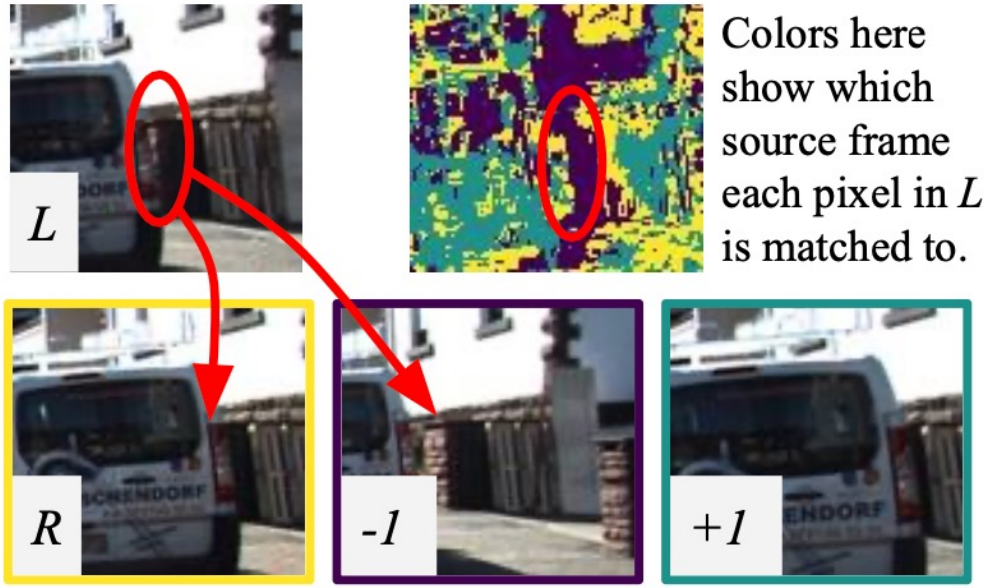
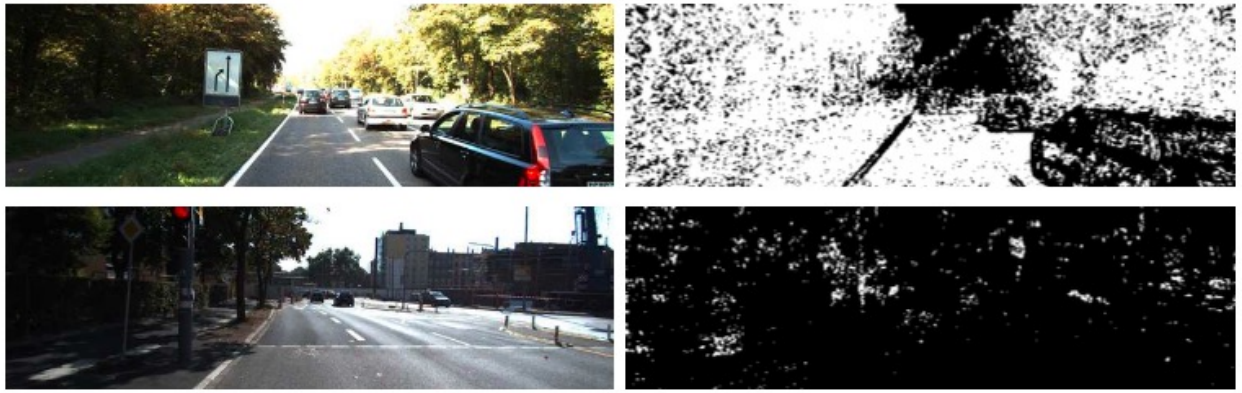


Colors here show which source frame each pixel in L is matched to.

$$L_p = \min_{t'} pe(I_t, I_{t' \to t})$$

Method

2. Auto-Masking Stationary Pixels



Black pixels are removed from the loss (*i.e.* $\mu = 0$)

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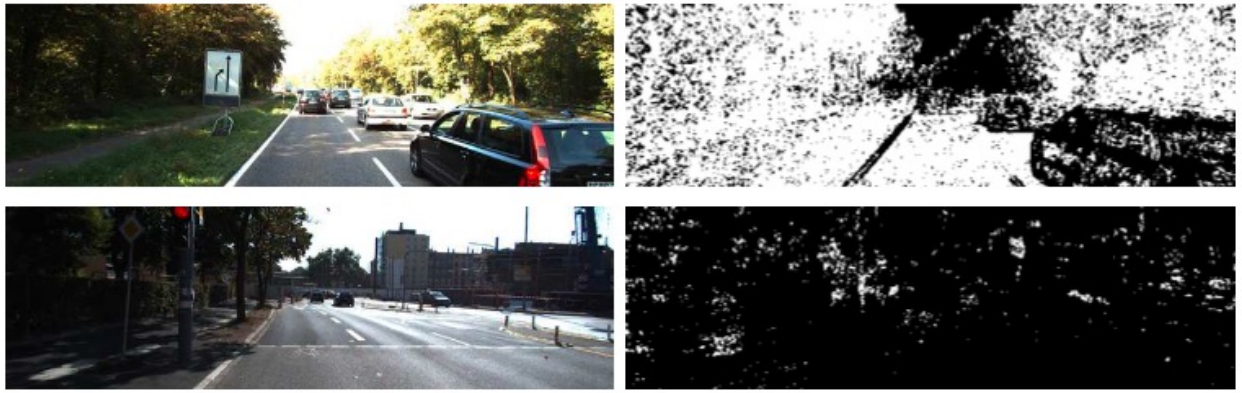

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$$\mu = \left[\min_{t'} pe(I_t, I_{t' \to t}) < \min_{t'} pe(I_t, I_{t'}) \right]$$

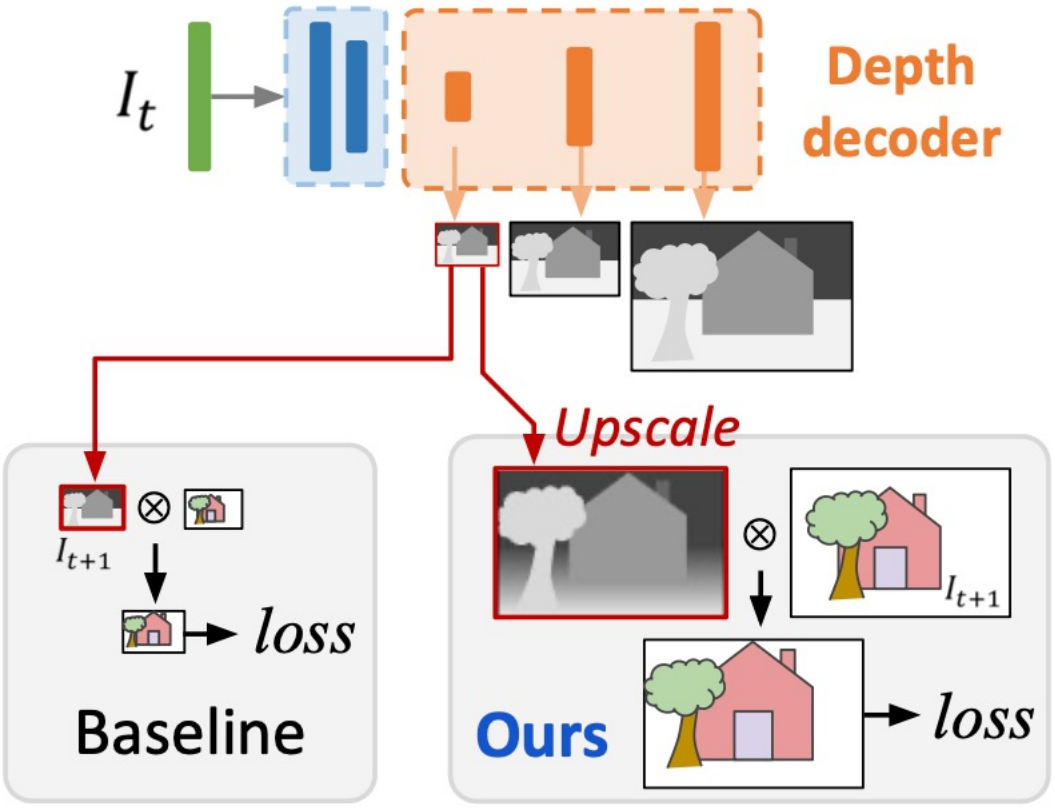
[ ] is the Iverson bracket.

$$[P] = \begin{cases} 1 & \text{if } P \text{ is true;} \\ 0 & \text{otherwise.} \end{cases}$$

This function is defined to take the value 1 for the values of the variables for which the statement is true, and takes the value 0 otherwise.

Method

3. Multi-scale Estimation



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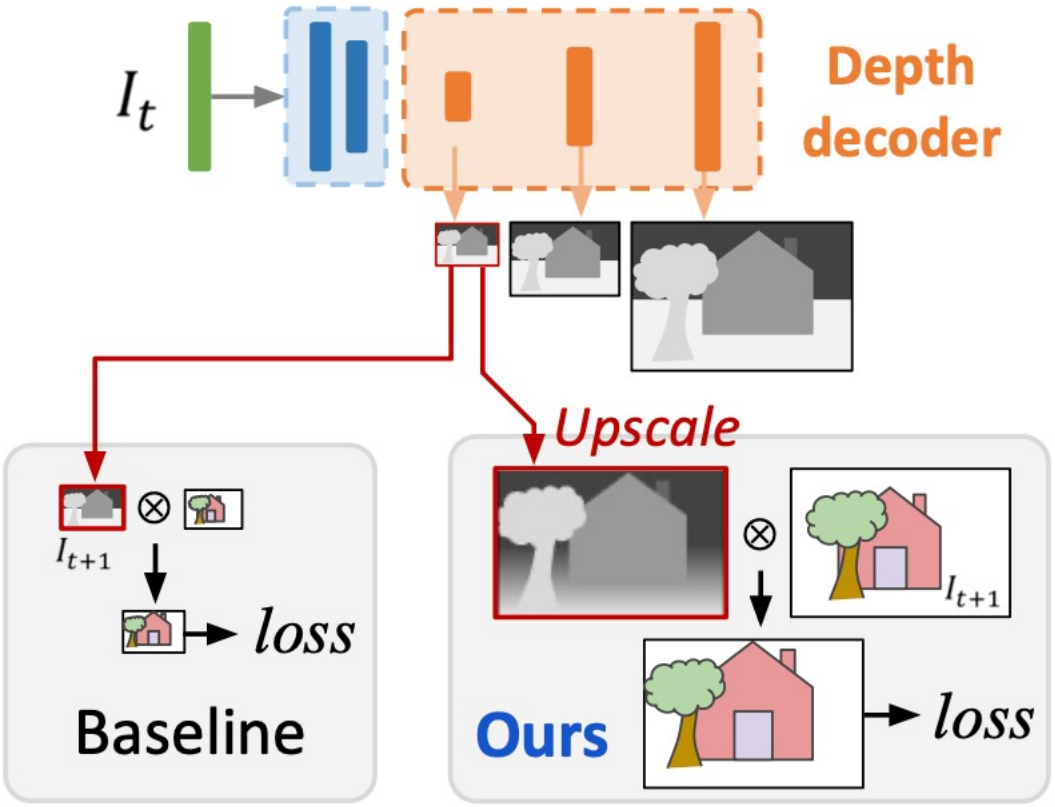

- Final Training Loss

$$L = \mu L_p + \lambda L_s$$

Method

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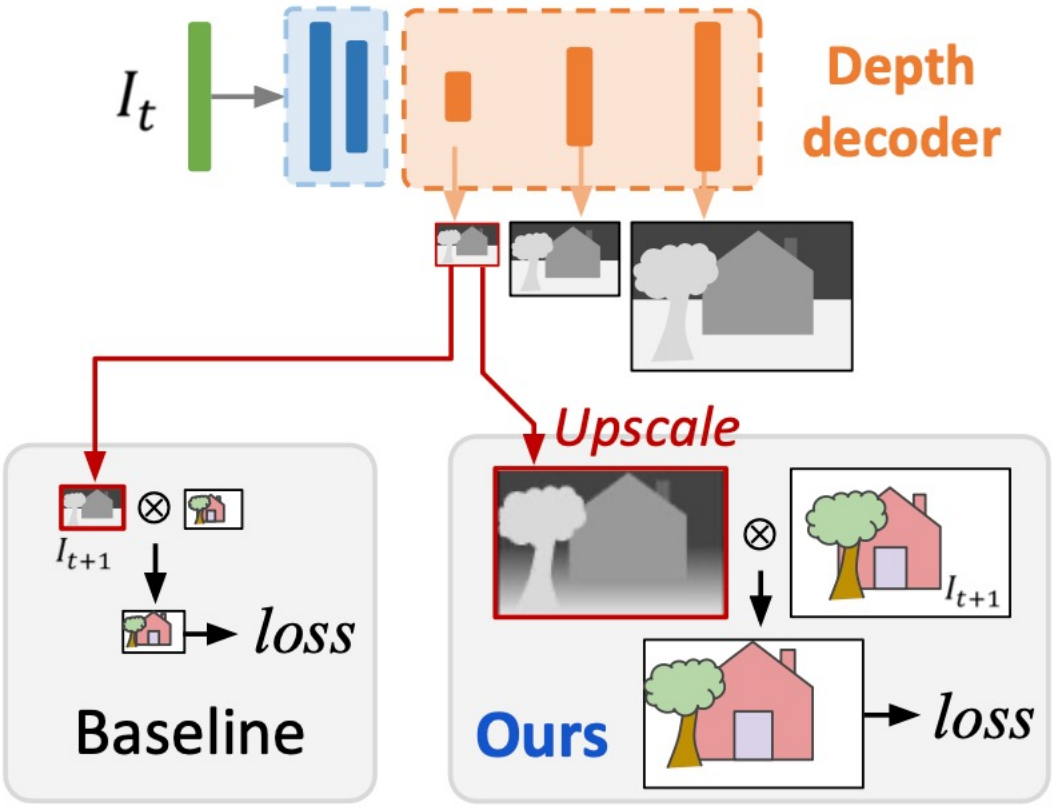

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$$pe(I_a, I_b) = \frac{\alpha}{2}(1 - \text{SSIM}(I_a, I_b)) + (1 - \alpha)\|I_a - I_b\|_1$$

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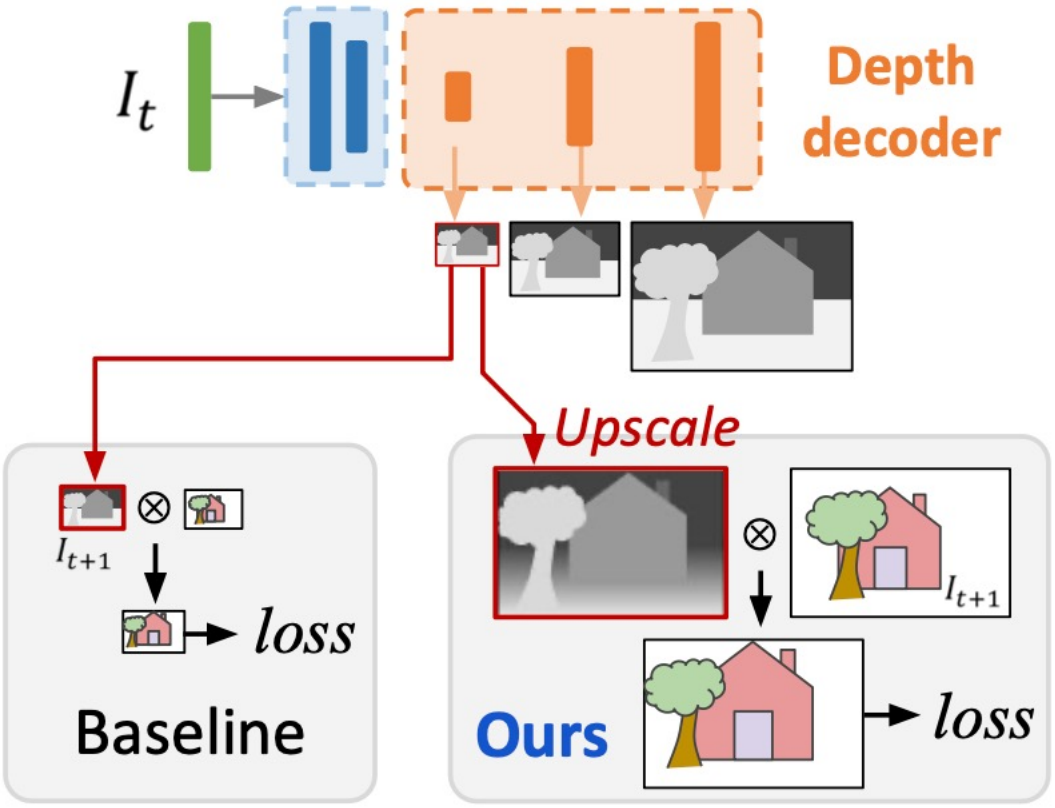

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$$L_s = |\partial_x d_t^*| \, e^{-|\partial_x I_t|} + |\partial_y d_t^*| \, e^{-|\partial_y I_t|}$$

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Experiments

- **RMSE** $= \sqrt{\frac{1}{|N|}\sum_{i \in N} \| d_i - d_i^* \|^2}$,
- **RMSE log** $= \sqrt{\frac{1}{|N|}\sum_{i \in N} \| \log(d_i) - \log(d_i^*) \|^2}$,
- **Abs Rel** $= \frac{1}{|N|}\sum_{i \in N} \frac{|d_i - d_i^*|}{d_i^*}$,
- **Sq Rel** $= \frac{1}{|N|}\sum_{i \in N} \frac{\|d_i - d_i^*\|^2}{d_i^*}$,
- **Accuracies:** % of d_i s.t. $\max(\frac{d_i}{d_i^*}, \frac{d_i^*}{d_i}) = \delta < thr$,

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Method	Train	Abs Rel	Sq Rel	RMSE	RMSE log	$\delta < 1.25$	$\delta < 1.25^2$	$\delta < 1.25^3$
Eigen [9]	D	0.203	1.548	6.307	0.282	0.702	0.890	0.890
Liu [36]	D	0.201	1.584	6.471	0.273	0.680	0.898	0.967
Klodt [28]	D*M	0.166	1.490	5.998	-	0.778	0.919	0.966
AdaDepth [45]	D*	0.167	1.257	5.578	0.237	0.771	0.922	0.971
Kuznietsov [30]	DS	0.113	0.741	4.621	0.189	0.862	0.960	0.986
DVSO [68]	D*S	0.097	0.734	4.442	0.187	0.888	0.958	0.980
SVSM FT [39]	DS	0.094	0.626	4.252	0.177	0.891	0.965	0.984
Guo [16]	DS	0.096	0.641	4.095	0.168	0.892	0.967	0.986
DORN [10]	D	**0.072**	**0.307**	**2.727**	**0.120**	**0.932**	**0.984**	**0.994**
Zhou [76]†	M	0.183	1.595	6.709	0.270	0.734	0.902	0.959
Yang [70]	M	0.182	1.481	6.501	0.267	0.725	0.906	0.963
Mahjourian [40]	M	0.163	1.240	6.220	0.250	0.762	0.916	0.968
GeoNet [71]†	M	0.149	1.060	5.567	0.226	0.796	0.935	0.975
DDVO [62]	M	0.151	1.257	5.583	0.228	0.810	0.936	0.974
DF-Net [78]	M	0.150	1.124	5.507	0.223	0.806	0.933	0.973
LEGO [69]	M	0.162	1.352	6.276	0.252	-	-	-
Ranjan [51]	M	0.148	1.149	5.464	0.226	0.815	0.935	0.973
EPC++ [38]	M	0.141	1.029	5.350	0.216	0.816	0.941	0.976
Struct2depth '(M)' [5]	M	0.141	1.026	5.291	0.215	0.816	0.945	0.979
Monodepth2 w/o pretraining	M	0.132	1.044	5.142	0.210	0.845	0.948	0.977
Monodepth2	M	**0.115**	**0.903**	**4.863**	**0.193**	**0.877**	**0.959**	**0.981**
Monodepth2 (1024 × 320)	M	**0.115**	**0.882**	**4.701**	**0.190**	**0.879**	**0.961**	**0.982**
Garg [12]†	S	0.152	1.226	5.849	0.246	0.784	0.921	0.967
Monodepth R50 [15]†	S	0.133	1.142	5.533	0.230	0.830	0.936	0.970
StrAT [43]	S	0.128	1.019	5.403	0.227	0.827	0.935	0.971
3Net (R50) [50]	S	0.129	0.996	5.281	0.223	0.831	0.939	0.974
3Net (VGG) [50]	S	0.119	1.201	5.888	0.208	0.844	0.941	**0.978**
SuperDepth + pp [47] (1024 × 382)	S	0.112	0.875	**4.958**	**0.207**	0.852	0.947	0.977
Monodepth2 w/o pretraining	S	0.130	1.144	5.485	0.232	0.831	0.932	0.968
Monodepth2	S	**0.109**	**0.873**	4.960	0.209	**0.864**	**0.948**	0.975
Monodepth2 (1024 × 320)	S	**0.107**	**0.849**	**4.764**	**0.201**	**0.874**	**0.953**	0.977
UnDeepVO [33]	MS	0.183	1.730	6.57	0.268	-	-	-
Zhan FullNYU [73]	D*MS	0.135	1.132	5.585	0.229	0.820	0.933	0.971
EPC++ [38]	MS	0.128	0.935	5.011	0.209	0.831	0.945	**0.979**
Monodepth2 w/o pretraining	MS	0.127	1.031	5.266	0.221	0.836	0.943	0.974
Monodepth2	MS	**0.106**	**0.818**	**4.750**	**0.196**	**0.874**	**0.957**	**0.979**
Monodepth2 (1024 × 320)	MS	**0.106**	**0.806**	**4.630**	**0.193**	**0.876**	**0.958**	**0.980**

Table 1. **Quantitative results.** Comparison of our method to existing methods on KITTI 2015 [13] using the Eigen split. Best results in each category are in **bold**; second best are underlined.

All results here are presented without post-processing [15]; see supplementary Section F for improved post-processed results. While our contributions are designed for monocular training, we still gain high accuracy in the stereo-only category.

We additionally show we can get higher scores at a larger 1024 × 320 resolution, similar to [47] – see supplementary Section G. These high resolution numbers are bolded if they beat all other models, including our low-res versions.

Legend

D – Depth supervision
D* – Auxiliary depth supervision
S – Self-supervised stereo supervision
M – Self-supervised mono supervision
† – Newer results from github.
+ pp – With post-processing

Experiments

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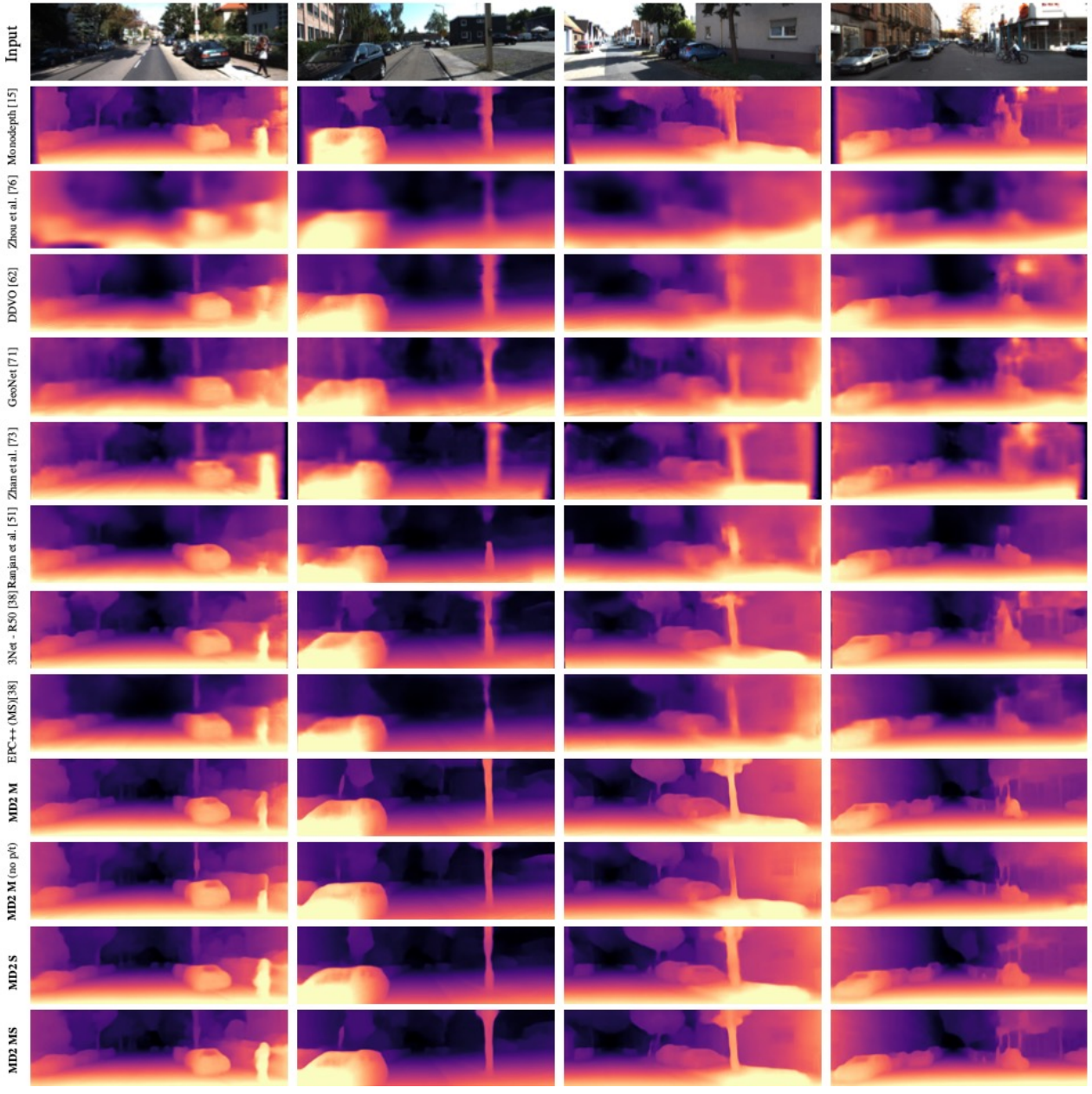
- **Abs Rel** $= \frac{1}{|N|}\sum_{i \in N} \frac{|d_i - d_i^*|}{d_i^*}$,
- **Sq Rel** $= \frac{1}{|N|}\sum_{i \in N} \frac{\|d_i - d_i^*\|^2}{d_i^*}$,
- **Accuracies:** % of d_i s.t. $\max(\frac{d_i}{d_i^*}, \frac{d_i^*}{d_i}) = \delta < thr$,

		Auto-masking	Min. reproj.	Full-res multi-scale	Pretrained	Full Eigen split	Abs Rel	Sq Rel	RMSE	RMSE log	$\delta < 1.25$	$\delta < 1.25^2$	$\delta < 1.25^3$
(a)	Baseline				✓		0.140	1.610	5.512	0.223	0.852	0.946	0.973
	Baseline + min reproj.		✓		✓		0.122	1.081	5.116	0.199	0.866	0.957	0.980
	Baseline + automasking	✓					0.124	0.936	5.010	0.206	0.858	0.952	0.977
	Baseline + full-res m.s.			✓	✓		0.124	1.170	5.249	0.203	0.865	0.953	0.978
	Monodepth2 w/o min reprojection	✓		✓	✓		0.117	0.878	4.846	0.196	0.870	0.957	0.980
	Monodepth2 w/o auto-masking		✓	✓	✓		0.120	1.097	5.074	0.197	0.872	0.956	0.979
	Monodepth2 w/o full-res m.s.	✓	✓		✓		0.117	**0.866**	4.864	0.196	0.871	0.957	**0.981**
	Monodepth2 with [76]'s mask		✓	✓	✓		0.123	1.177	5.210	0.200	0.869	0.955	0.978
	Monodepth2 smaller (416 × 128)	✓	✓	✓	✓		0.128	1.087	5.171	0.204	0.855	0.953	0.978
	Monodepth2 (full)	✓	✓	✓	✓		**0.115**	0.903	**4.863**	**0.193**	**0.877**	**0.959**	**0.981**
(b)	Baseline w/o pt						0.150	1.585	5.671	0.234	0.827	0.938	0.971
	Monodepth2 w/o pt	✓	✓	✓			**0.132**	**1.044**	**5.142**	**0.210**	**0.845**	**0.948**	**0.977**
(c)	Baseline (full Eigen dataset)				✓	✓	0.146	1.876	5.666	0.230	0.848	0.945	0.972
	Monodepth2 (full Eigen dataset)	✓	✓	✓	✓	✓	**0.116**	**0.918**	**4.872**	**0.193**	**0.874**	**0.959**	**0.981**

Table 2. **Ablation.** Results for different variants of our model (**Monodepth2**) with monocular training on KITTI 2015 [13] using the Eigen split. **(a)** The baseline model, with none of our contributions, performs poorly. The addition of our minimum reprojection, auto-masking and full-res multi-scale components, significantly improves performance. **(b)** Even without ImageNet pretrained weights, our much simpler model brings large improvements above the baseline – see also Table 1. **(c)** If we train with the full Eigen dataset (instead of the subset introduced for monocular training by [76]) our improvement over the baseline increases.

Experiments



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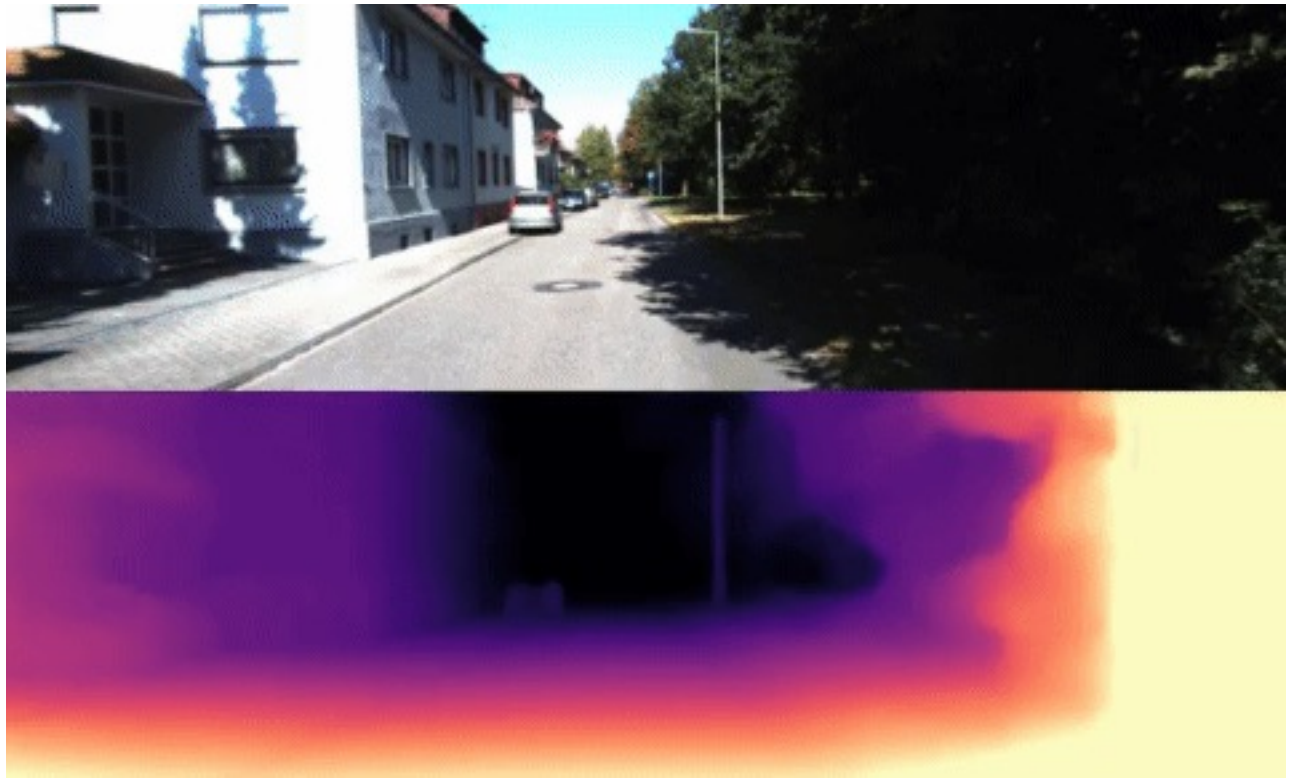
- Self-supervised Monocular Depth Estimation



Q & A