

Unsupervised Learning of Monocular Depth and Ego-Motion Using Multiple Masks

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2019 IEEE

International Conference on **Robotics and Automation**

May 20-24, 2019 Montreal, Canada



Task

> Unsupervised learning of depth and ego-motion from monocular video

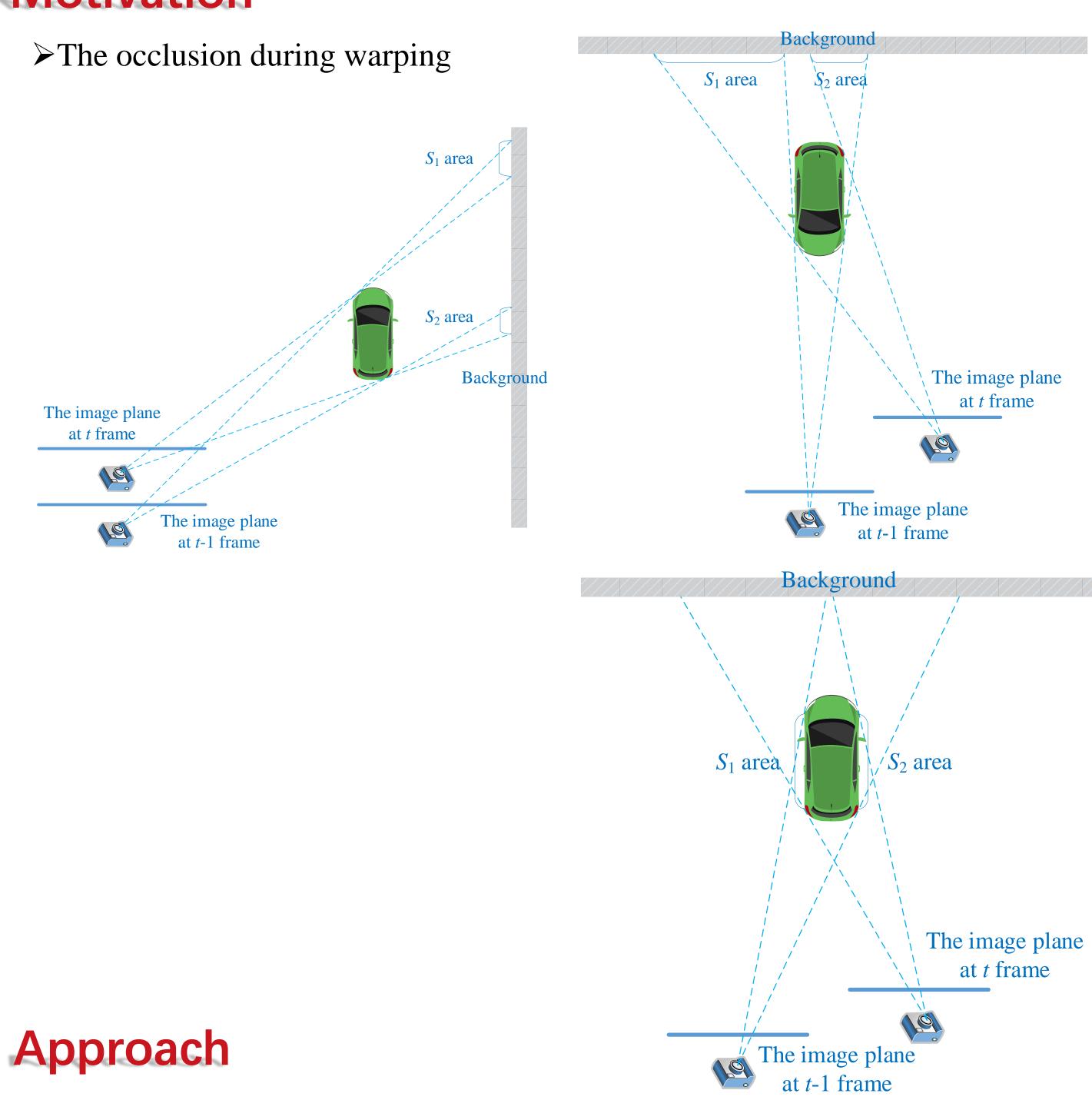
Preliminary

> Zhou et al. proposed to use view synthesis as supervision

Challenge

> 3D Geometric cues are modeled without any ground truth

Motivation



➤ The overview

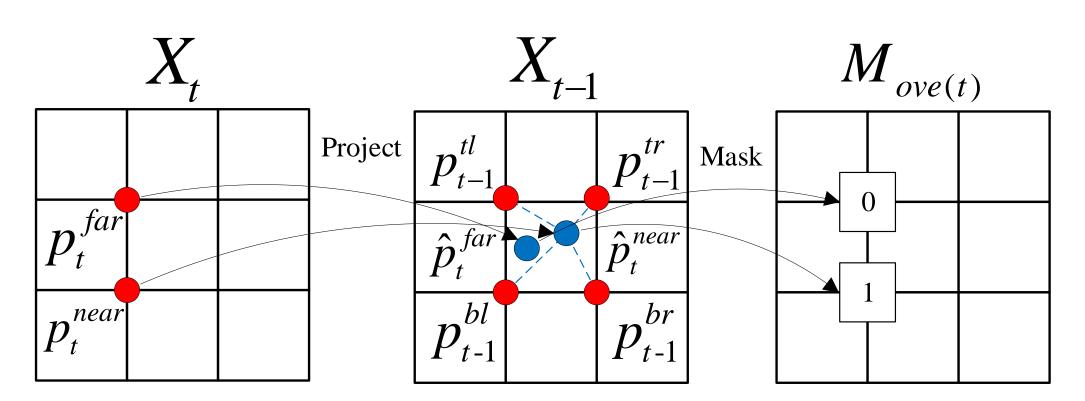
Blank mask $M_{bla(t)}$ Project Input image X_t Reconstruction loss Estimated ego-motion T_r^{-1} Estimated depth D_t for every pixels $L_{\text{rec}(t)}$ Estimated depth D_{t-1} Estimated ego-motion T_t Input image X_{t-1} Project Overlap mask $M_{ove(t)}$ SSIM loss for every pixels Edge mask $M_{edg(t)}$ $L_{SSIM(t)}$

*The Figure just shows the process in one direction (t) and the other direction (t-1) is also used and similar.

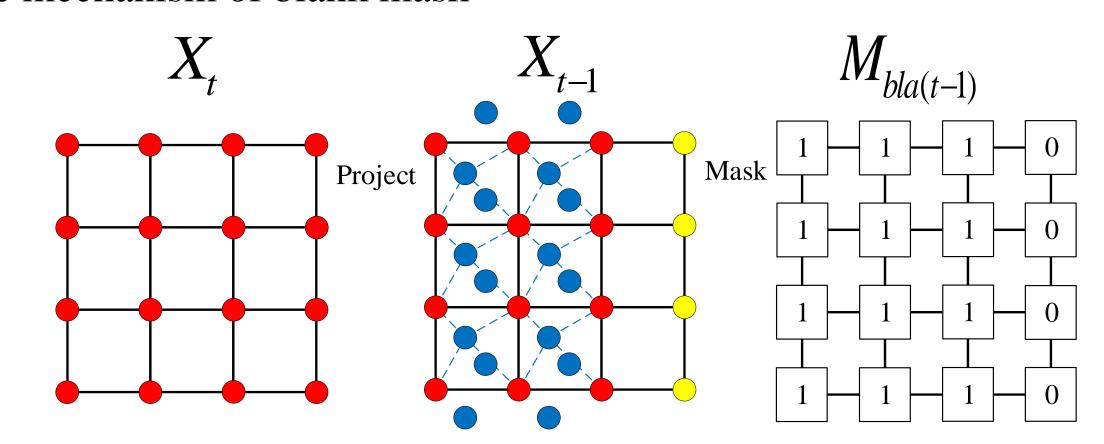
Reconstructed image X_t

- > Our system uses consecutive two frames from monocular video to reconstruct the images based on the depth and ego-motion estimated by the depth estimation network and the pose estimation network, obtaining several masks at the same time.
- > Next, the reconstructed image, the original image, and several masks are used to calculate the two main loss functions for backpropagation.

The mechanism of overlap mask



The mechanism of blank mask



➤ Image reconstruction loss

$$L_{\text{rec}} = \sum_{ii} \left\| (X_t^{ij} - \hat{X}_t^{ij}) M_{edg(t)}^{ij} M_{ove(t)}^{ij} M_{bla(t)}^{ij} \right\|$$

>Structural similarity loss

$$L_{\text{SSIM}} = \sum_{ij} [1 - \text{SSIM}(X_t^{ij}, \hat{X}_t^{ij})] M_{edg(t)}^{ij} M_{ove(t)}^{ij} M_{bla(t)}^{ij}$$

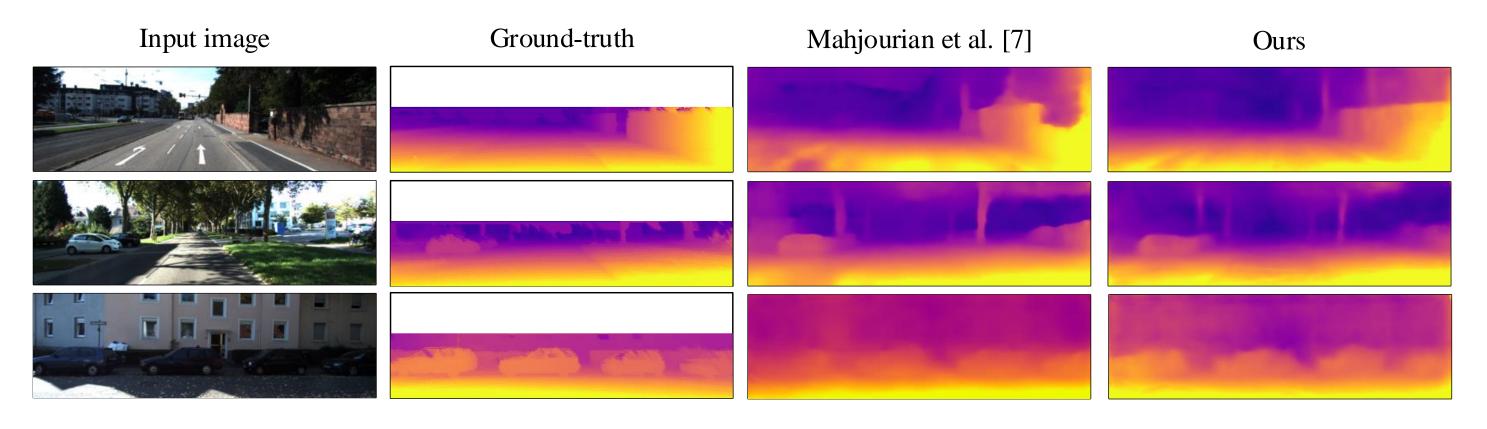
The common smoothness loss as in [7] and [16]

Results

Depth

Method	Supervised	Dataset	Error metric				Accuracy metric		
			Abs Rel	Sq Rel	RMSE	RMSE log	δ < 1.25	δ < 1.25 ²	$\delta < 1.25^{3}$
Godard et al. [9]	Stereo	K	0.148	1.344	5.927	0.247	0.803	0.922	0.964
Zhan et al. [10]	Stereo	K	0.144	1.391	5.869	0.241	0.803	0.928	0.969
Zhou et al. [12]	No	K	0.208	1.768	6.856	0.283	0.678	0.885	0.957
GeoNet [16]	No	K	0.164	1.303	6.090	0.247	0.765	0.919	0.968
Mahjourian et al. [7]	No	K	0.163	1.240	6.220	0.250	0.762	0.916	0.968
LEGO [17]	No	K	0.162	1.352	6.276	0.252	-	-	-
Ours	No	K	0.158	1.277	5.858	0.233	0.785	0.929	0.973
Ours +DN*	No	K	0.154	1.163	5.700	0.229	0.792	0.932	0.974

*DN means depth normalization from [18]. The best and the second best performance in each block are highlighted in blue and green.



≻Camera Pose

Method	Seq.09	Seq.10	
ORB-SLAM (full)	0.014 ± 0.008	0.012 ± 0.011	
ORB-SLAM (short)	0.064 ± 0.141	0.064 ± 0.130	
Zhou et al. [12]	0.021 ± 0.017	0.020 ± 0.015	
Mahjourian et al. [7]	0.013 ± 0.010	0.012 ± 0.011	
GeoNet [16]	0.012 ± 0.007	0.012 ± 0.009	
Ours	$\boldsymbol{0.009 \pm 0.005}$	$\boldsymbol{0.008 \pm 0.007}$	

➤ Visualization of the Overlap Mask and Blank Mask

