无监督且尺度一致的深度估计与视觉SLAM

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分享大岗

1. 单目无监督深度估计原理
2. 输出尺度不一致问题
3. 我们的解决方案
4. 用输出尺度一致的深度做视觉SLAM
5. 三维重构Demo

1. 单目无监督深度估计原理

根据训练数据分为三类：

1. Stereo Pair

   (Grag et al, ECCV 2016) Unsupervised CNN for Single View Depth Estimation: Geometry to Rescue

2. Monocular Video

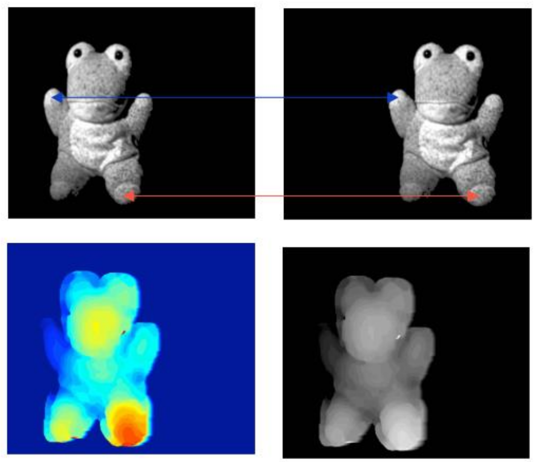
   (SfMLearner, CVPR 2017) Unsupervised Learning of Depth and Ego-Motion from Video

3. Stereo Video

   (Depth-VO-Feat, CVPR 18) Unsupervised Learning of Monocular Depth Estimation and Visual Odometry with Deep Feature Reconstruction

1. 单目无监督深度估计原理

- Recover depth from two views

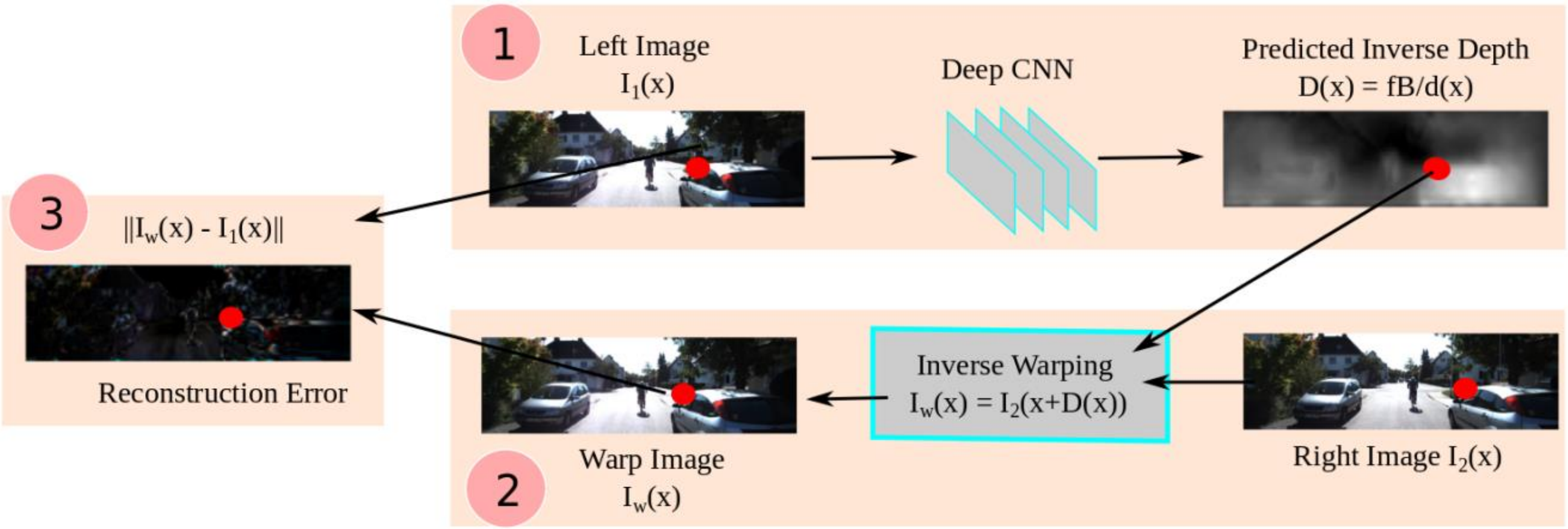


disparity

  - 1. Search for correspondences.
  - 2. Camera intrinsics and relative poses.
    - Known in Stereo Matching or solved by Structure-from-Motion.
  - 3. Depth and disparity are inverse. $D(x) = fB/d(x)$

1. 单目无监督深度估计原理

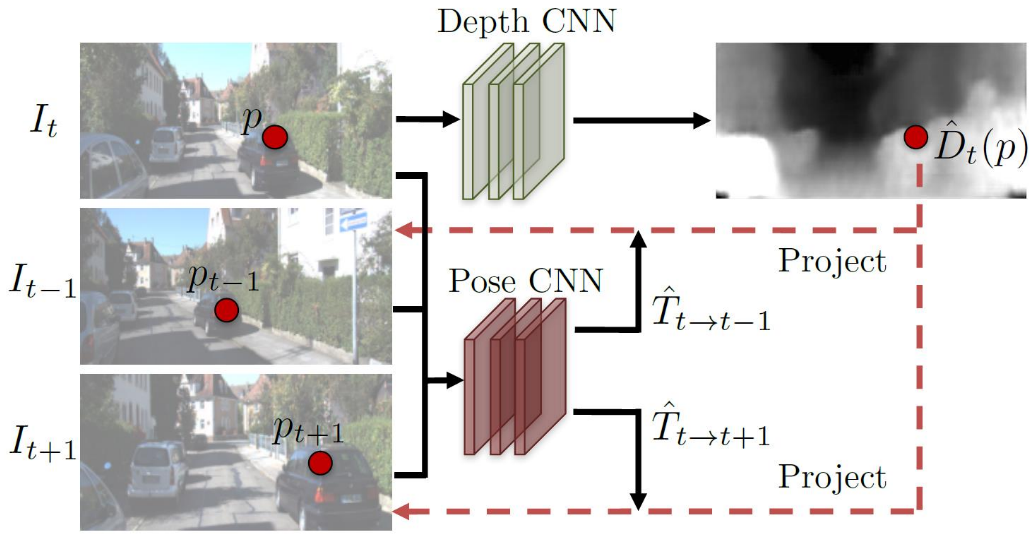
- Stereo Pair (Grag et al, ECCV 2016)



  - 1. Absolute scale.
  - 2. Occlusion issue.

1. 单目无监督深度估计原理

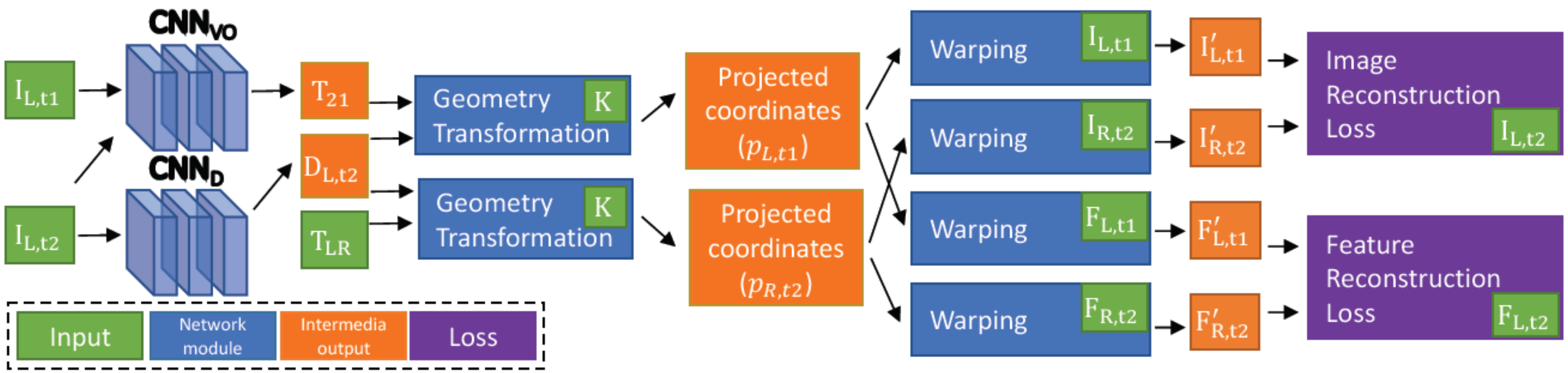
- Monocular Video (SfMLearner, CVPR 2017)



  - 1. No absolute scale. (scale ambiguity)
  - 2. Occlusion issue.
  - 3. Dynamics issue.
  - 4. Scale inconsistency issue. (cannot do visual odometry)

1. 单目无监督深度估计原理

- Stereo Video (Depth-VO-Feat, CVPR 2018)



  - Absolute scale.
  - Can do Visual Odometry.
  - Occlusion issue.
  - Dynamics issue.

1. 单目无监督深度估计原理

- Depth Results (copied from Depth-VO-Feat, CVPR 2018)

Method	Dataset	Supervision	Error metric				Accuracy metric		
			Abs Rel	SqRel	RMSE	RMSE log	$\delta < 1.25$	$\delta < 1.25^2$	$\delta < 1.25^3$
Depth: cap 80m									
Train set mean	K	Depth	0.361	4.826	8.102	0.377	0.638	0.804	0.894
Eigen *et al.* [5] Fine	K	Depth	0.203	1.548	6.307	0.282	0.702	0.890	0.958
Liu *et al.* [22]	K	Depth	0.201	1.584	6.471	0.273	0.680	0.898	0.967
Zhou *et al.* [44]	K	Mono.	0.208	1.768	6.856	0.283	0.678	0.885	0.957
Garg *et al.* [6]	K	Stereo	0.152	1.226	5.849	0.246	0.784	0.921	0.967
Godard *et al.* [9]	K	Stereo	0.148	1.344	5.927	0.247	0.803	0.922	0.964
Ours (Temporal)	K	Stereo	0.144	1.391	5.869	0.241	0.803	0.928	0.969
Ours (Full-NYUv2)	K	Stereo	0.135	1.132	5.585	0.229	0.820	0.933	0.971

  - "Garg et al. [6]" stands for (Grag et al, ECCV 2016)
  - "Zhou et al. [44]" stands for (SfMLearner, CVPR 2017)
  - "Ours" stand for (Depth-VO-Feat, CVPR 2018)

1. 单目无监督深度估计原理

- Pose results (SfMLearner, CVPR 2017)

Method	**Seq.** 09	**Seq.** 10
ORB-SLAM (full)	$\mathbf{0.014 \pm 0.008}$	$\mathbf{0.012 \pm 0.011}$
ORB-SLAM (short)	0.064 ± 0.141	0.064 ± 0.130
Mean Odom.	0.032 ± 0.026	0.028 ± 0.023
Ours	$\mathbf{0.021 \pm 0.017}$	$\mathbf{0.020 \pm 0.015}$

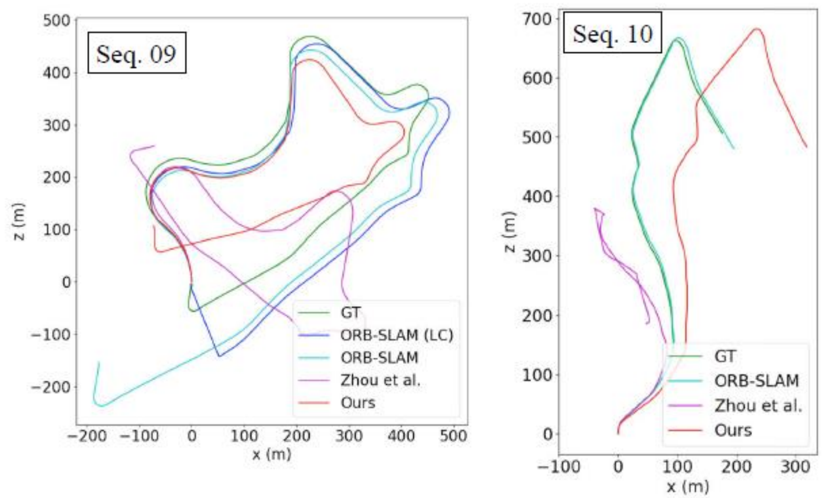
Table 3. Absolute Trajectory Error (ATE) on the KITTI odometry split averaged over all 5-frame snippets (lower is better). Our method outperforms baselines with the same input setting, but falls short of `ORB-SLAM (full)` that uses strictly more data.

1. 单目无监督深度估计原理

- Visual Odometry Results (Depth-VO-Feat, CVPR 2018)

Method	Seq. 09		Seq. 10	
	$t_{err}(\%)$	$r_{err}(°/100m)$	$t_{err}(\%)$	$r_{err}(°/100m)$
ORB-SLAM (LC) [26]	16.23	1.36	/	/
ORB-SLAM [26]	15.30	0.26	3.68	0.48
Zhou *et al.*[44]	17.84	6.78	37.91	17.78
Ours (Temporal)	11.93	3.91	12.45	3.46
Ours (Full-NYUv2)	11.92	3.60	12.62	3.43

Table 1. Visual odometry result evaluated on Sequence 09, 10 of KITTI Odometry dataset. t_{err} is average translational drift error. r_{err} is average rotational drift error.



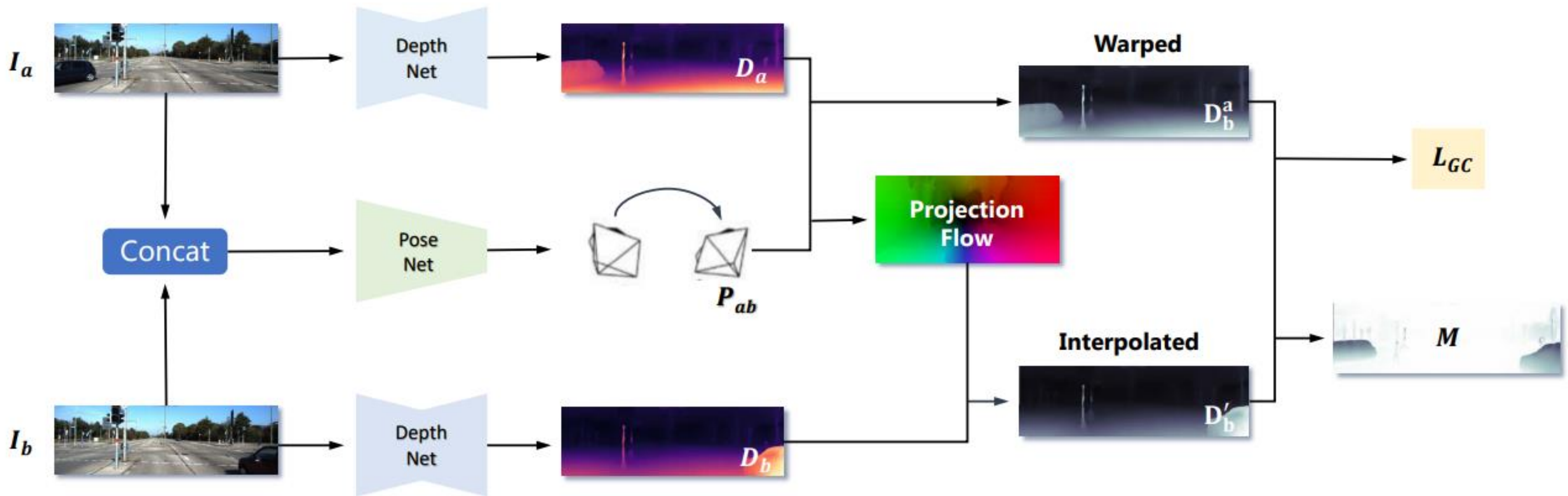
2. 输出尺度不一致问题

- 现象与影响
  - Predict depth and pose with varying scales on a sequence
  - Depth cannot be fused together for mapping
  - Poses cannot be concatenated for camera localization

- 造成问题的原因
  - Scale ambiguity
  - Photometric loss is scale-invariant
  - Training samples are independently processed.

3. 我们的解决方案

- SC-SfMLearner, NeurIPS 2019
  - Geometry Consistency Loss (for scale consistency)
  - Self Discovered Mask (for handling occlusion and dynamics)



3. 我们的解决方案

- SC-SfMLearner, NeurIPS 2019
  - Relative depth error

$$D_{\text{diff}}(p) = \frac{|D_b^a(p) - D_b'(p)|}{D_b^a(p) + D_b'(p)}$$

  - Geometry Consistency Loss

$$L_{GC} = \frac{1}{|V|} \sum_{p \in V} D_{\text{diff}}(p),$$

  - Self Discovered Mask

$$M = 1 - D_{\text{diff}},$$

3. 我们的解决方案

- SC-SfMLearner, NeurIPS 2019
  - Depth and Mask Visualization

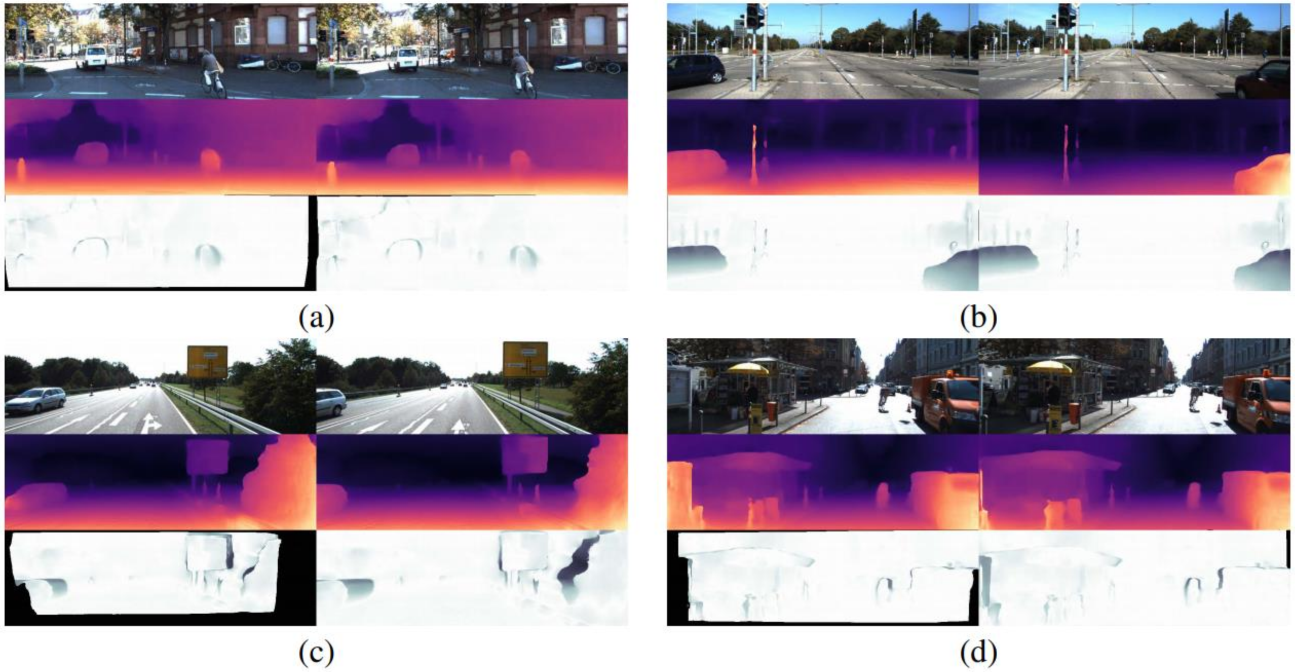


Figure 2: Visual results. Top to bottom: sample image, estimated depth, self-discovered mask. The proposed mask can effectively identify occlusions and moving objects.

3. 我们的解决方案

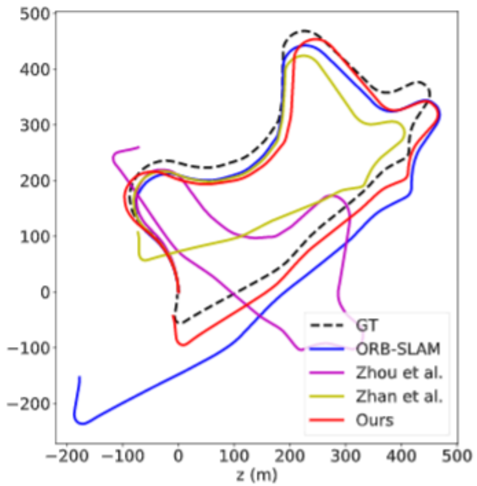
- SC-SfMLearner, NeurIPS 2019
  - Depth results

Methods	Dataset	Error ↓				Accuracy ↑		
		AbsRel	SqRel	RMS	RMSlog	< 1.25	$< 1.25^2$	$< 1.25^3$
Eigen et al. [4]	K (D)	0.203	1.548	6.307	0.282	0.702	0.890	0.958
Liu et al. [5]	K (D)	0.202	1.614	6.523	0.275	0.678	0.895	0.965
Garg et al. [21]	K (B)	0.152	1.226	5.849	0.246	0.784	0.921	0.967
Kuznietsov et al. [18]	K (B+D)	**0.113**	**0.741**	**4.621**	**0.189**	**0.862**	**0.960**	**0.986**
Godard et al. [22]	K (B)	0.148	1.344	5.927	0.247	0.803	0.922	0.964
Godard et al. [22]	CS+K (B)	0.124	1.076	5.311	0.219	0.847	0.942	0.973
Zhan et al. [17]	K (B)	0.144	1.391	5.869	0.241	0.803	0.928	0.969
Zhou et al. [6]	K (M)	0.208	1.768	6.856	0.283	0.678	0.885	0.957
Yang et al. [29] (J)	K (M)	0.182	1.481	6.501	0.267	0.725	0.906	0.963
Mahjourian et al. [7]	K (M)	0.163	1.240	6.220	0.250	0.762	0.916	0.968
Wang et al. [16]	K (M)	0.151	1.257	5.583	0.228	0.810	0.936	0.974
Geonet-VGG [8] (J)	K (M)	0.164	1.303	6.090	0.247	0.765	0.919	0.968
Geonet-Resnet [8] (J)	K (M)	0.155	1.296	5.857	0.233	0.793	0.931	0.973
DF-Net [9] (J)	K (M)	0.150	1.124	5.507	0.223	0.806	0.933	0.973
CC [10] (J)	K (M)	0.140	**1.070**	**5.326**	**0.217**	0.826	0.941	**0.975**
Ours	K (M)	**0.137**	1.089	5.439	**0.217**	**0.830**	**0.942**	**0.975**
Zhou et al. [6]	CS+K (M)	0.198	1.836	6.565	0.275	0.718	0.901	0.960
Yang et al. [29] (J)	CS+K (M)	0.165	1.360	6.641	0.248	0.750	0.914	0.969
Mahjourian et al. [7]	CS+K (M)	0.159	1.231	5.912	0.243	0.784	0.923	0.970
Wang et al. [16]	CS+K (M)	0.148	1.187	5.496	0.226	0.812	0.938	0.975
Geonet-Resnet [8] (J)	CS+K (M)	0.153	1.328	5.737	0.232	0.802	0.934	0.972
DF-Net [9] (J)	CS+K (M)	0.146	1.182	5.215	0.213	0.818	0.943	**0.978**
CC [10] (J)	CS+K (M)	0.139	**1.032**	**5.199**	0.213	0.827	0.943	0.977
Ours	CS+K (M)	**0.128**	1.047	5.234	**0.208**	**0.846**	**0.947**	0.976

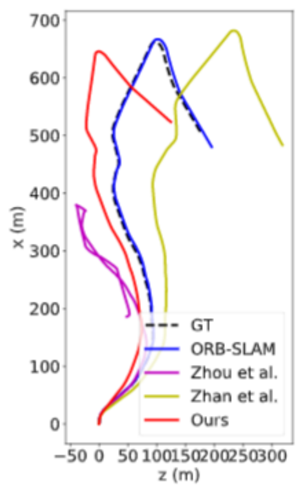
3. 我们的解决方案

- SC-SfMLearner, NeurIPS 2019
  - Visual Odometry Results

Methods	Seq. 09		Seq. 10	
	t_{err} (%)	r_{err} (°/100m)	t_{err} (%)	r_{err} (°/100m)
ORB-SLAM [11]	15.30	0.26	3.68	0.48
Zhou et al. [6]	17.84	6.78	37.91	17.78
Zhan et al. [17]	11.93	3.91	12.45	**3.46**
Ours (K)	11.25	5.85	10.10	8.56
Ours (CS+K)	**8.23**	**3.83**	**9.96**	6.90



(a) sequence 09



(b) sequence 10

3. 我们的解决方案

- SC-SfMLearner, NeurIPS 2019
  - Depth估计存在的问题
    - Although consistent, but the scale is still unknown
  - Visual Odometry存在的问题
    - Lack of multi-view optimization
    - Heavy drifts in long videos

4. 用输出尺度一致的深度做视觉SLAM

- Pseudo-RGBD SLAM (extension to SC-SfMLearner)
  - 系统介绍
    - 使用ORB-SLAM2 （RGB-D）作为框架
    - 用网络估计的depth作为输入
    - 用网络估计的pose来作为tracking的初值
  - 系统优缺点
    - 解决了单目SLAM中的初始化问题
    - 利用bundle adjustment实现multi-frame optimization
    - 利用loop closing实现drift correction
    - 创建Dense地图

4. 用输出尺度一致的深度做视觉SLAM

- Pseudo-RGBD SLAM (extension to SC-SfMLearner)
  - Visual Odometry Results on KITTI

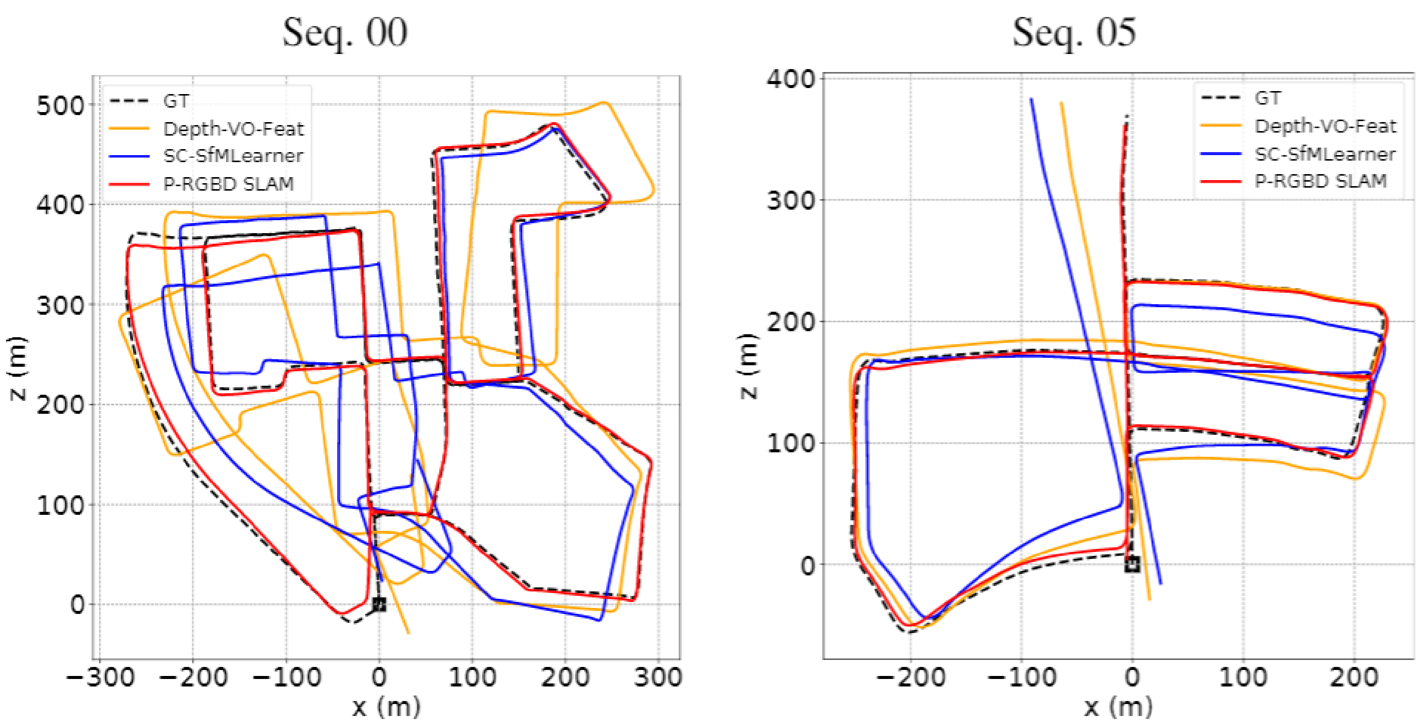
    Models are trained on (00-08). * denotes sequences that contain loops. G denotes geometric methods, M / B denotes models trained on Monocular / Binocular videos.

    7-DoF optimization is used for monocular methods (M).

Seq	VISO2-M [25] (G)		Depth-VO-Feat [9] (B)		SfMLearner [1] (M)		DW [22] (M)		SC-SfMLearner Ours (M)		P-RGBD SLAM Ours (M+G)	
	t_{err}	r_{err}	t_{err}	r_{err}	t_{err}	r_{err}	t_{err}	r_{err}	t_{err}	r_{err}	t_{err}	r_{err}
00*	10.53	2.73	6.23	2.44	21.32	6.19	11.61	3.85	6.95	2.92	**2.15**	**0.81**
02*	18.71	1.19	6.59	2.26	24.10	4.18	6.99	2.23	6.20	2.72	**2.32**	**0.73**
03	30.21	2.21	15.76	10.62	12.56	4.52	13.26	7.61	5.11	4.20	**2.47**	**1.26**
04	34.05	1.78	**3.14**	2.02	4.32	3.28	6.30	3.18	4.13	2.77	3.58	**1.84**
05*	13.16	3.65	4.94	2.34	12.99	4.66	14.36	4.22	5.91	2.96	**1.67**	**0.50**
06*	17.69	1.93	5.80	2.06	15.55	5.58	4.92	1.38	5.98	2.83	**2.48**	**1.14**
07*	10.80	4.67	6.49	3.56	12.61	6.31	14.27	9.08	7.57	3.96	**0.73**	**0.47**
08	13.85	2.52	5.45	2.39	10.66	3.75	8.09	1.83	6.84	3.10	**4.39**	**1.37**
09*	18.06	1.25	11.89	3.60	11.32	4.07	7.89	2.22	7.31	3.05	**5.08**	**1.05**
10	26.10	3.26	12.82	3.41	15.25	4.06	13.18	2.54	7.79	4.90	**4.32**	**2.34**
Avg	15.25	2.34	6.71	2.60	17.27	4.73	9.69	3.00	6.60	3.02	**2.85**	**0.95**

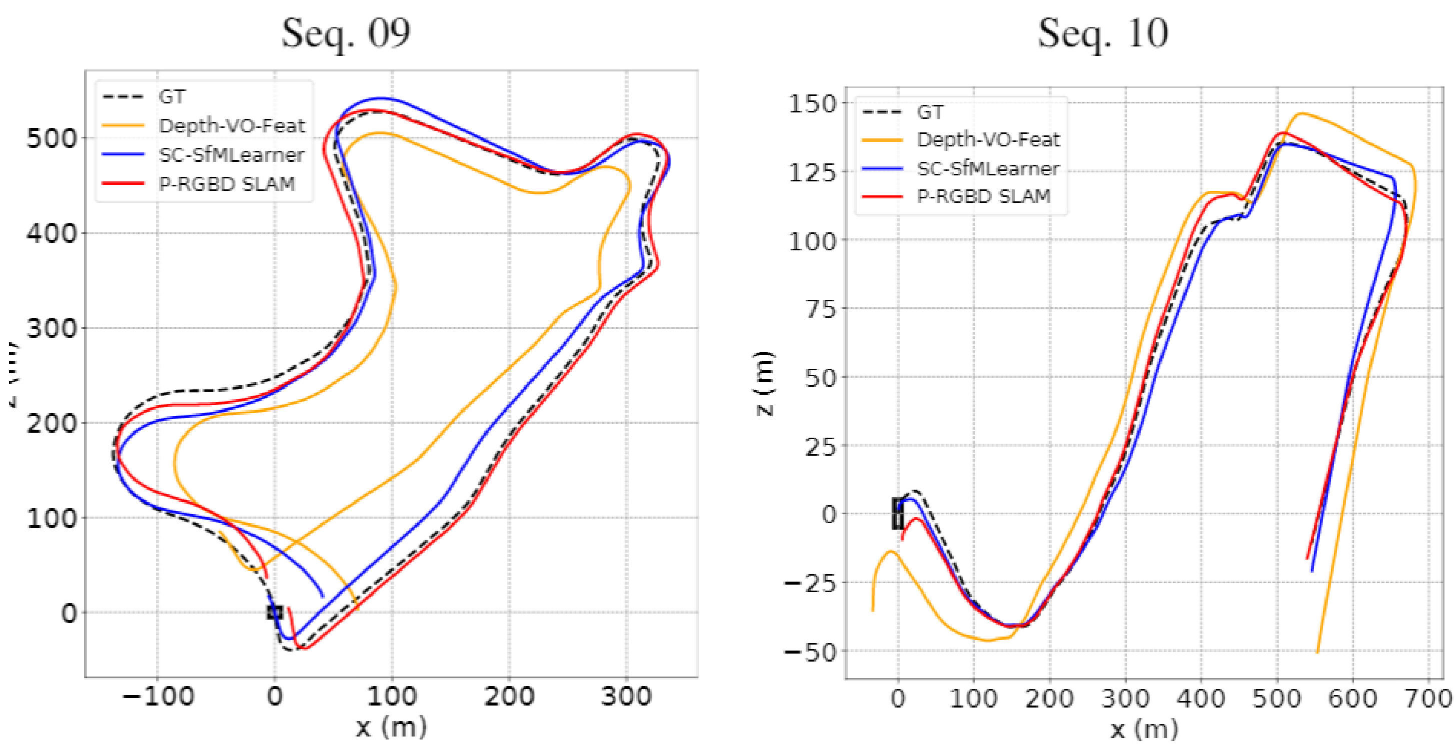
4. 用输出尺度一致的深度做视觉SLAM

- Pseudo-RGBD SLAM (extension to SC-SfMLearner)
  - Visualization of trajectory (loop detected sequences)



4. 用输出尺度一致的深度做视觉SLAM

- Pseudo-RGBD SLAM (extension to SC-SfMLearner)
  - Visualization of trajectory (no loop or loop not detected)



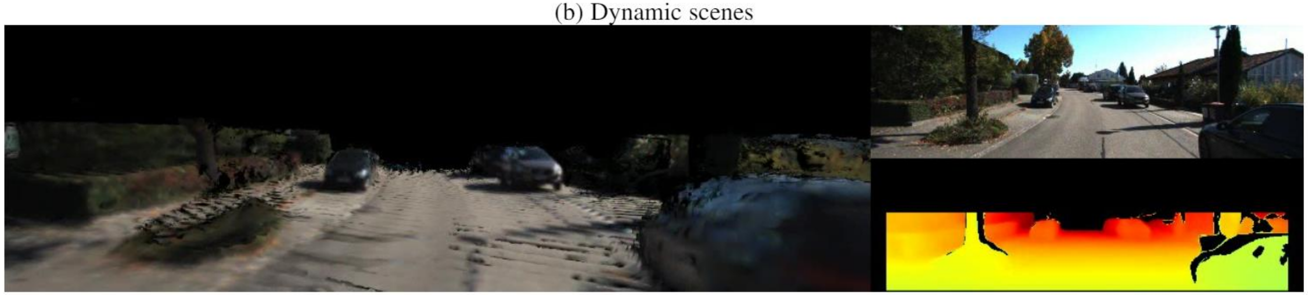
5. 三维重构Demo

- Screen shot

  Left is the reconstructed 3D model. Top right is input RGB image, Bottom right is the estimated depth map (with our mask).

(a) Static scenes

(b) Dynamic scenes



- Full Video demo link: [Here]

相关链接

- 论文地址：
  - https://arxiv.org/abs/1908.10553
- 代码地址：
  - https://github.com/JiawangBian/SC-SfMLearner-Release
- KITTI VO Evaluation Code (python):
  - https://github.com/Huangying-Zhan/kitti-odom-eval

Q & A

SUB CRUCE LUMEN

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