



Learning to Segment Rigid Motions from Two Frames

Gengshan Yang and Deva Ramanan

Code available at:

https://github.com/gengshan-y/ rigidmask

Goal: Scene decomposition based on two-frame rigidity



Input



Rigid mask and motion (blue: ego-motion; red: object motion)



Moving foreground



Static background reconstruction

Related work



Geometric Motion segmentation Appearance-based detectors

(2D motion angle) [1,2]



(fires on objects *able to move*)



Ours (fires only on *moving* objects)

[1] P Bideau and E Learned-Miller. "It's moving! A probabilistic model for causal motion segmentation in moving camera videos." ECCV. 2016. [2] J Wulff, L Sevilla-Lara, MJ Black. "Optical flow in mostly rigid scenes." CVPR. 2017.

Challenges

Two frame overlay

- Degeneracies in geometric motion segmentation.
 - Epipolar constraints fail when translation is close to zero.
 - o Points moving along epipolar lines cannot be distinguished.
- Noisy motion correspondences and camera egomotion estimates.



Flow-triangulated reconstruction

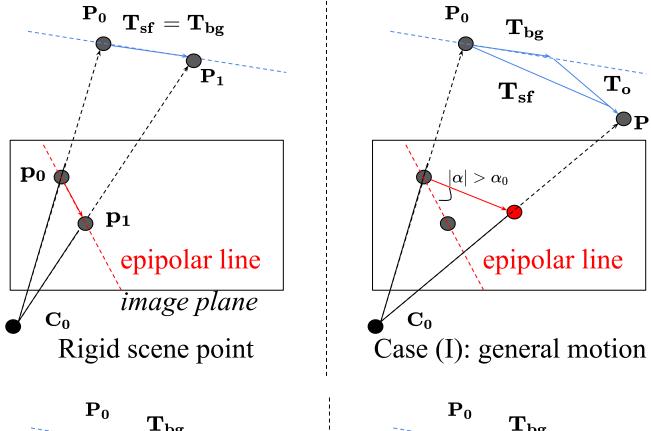


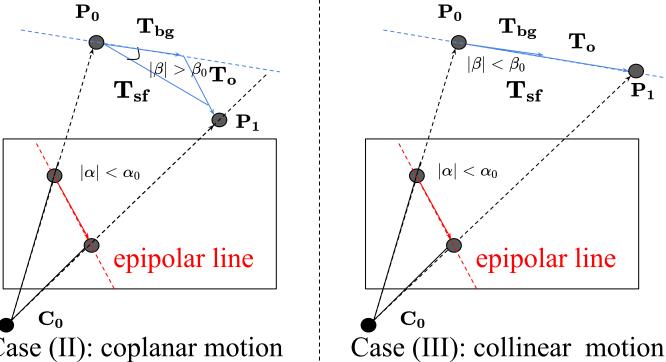
Sampson err. (p1,p2;F) (white \rightarrow moving)

Analysis

When can a moving scene point P be identified from a moving camera?

 $\mathbf{T_{bg}} := -\mathbf{T_c}$ (bg motion due to camera motion) (3D scene flow assuming no cam rotation)

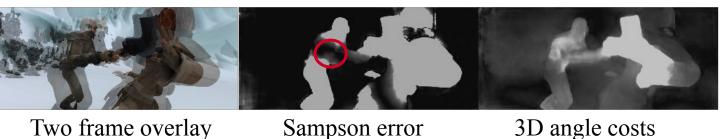




Degeneracies and rigidity cost maps

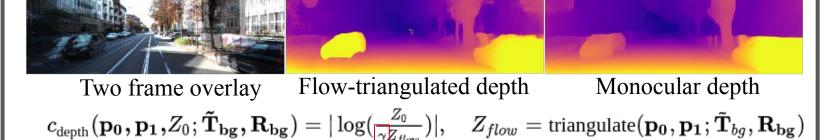
Case (II): coplanar motion

- Small translation: Rotational homography $c_{\rm H}({\bf p_0},{\bf p_1};{\bf H_R})$
- Coplanar motion (ambiguous w/o relative depth $\tau=Z1/Z0$)



 $c_{ ext{3D-angle}}(\mathbf{p_0},\mathbf{p_1}, au;\mathbf{ ilde{T}_{bg}},\mathbf{H_R}) = |\angle(\mathbf{ ilde{T}_{bg}},\mathbf{ ilde{T}_{sf}})|, \quad \mathbf{ ilde{T}_{sf}} = \mathbf{K_0}^{-1}(au\mathbf{H_R}\mathbf{p_1} - \mathbf{p_0})$

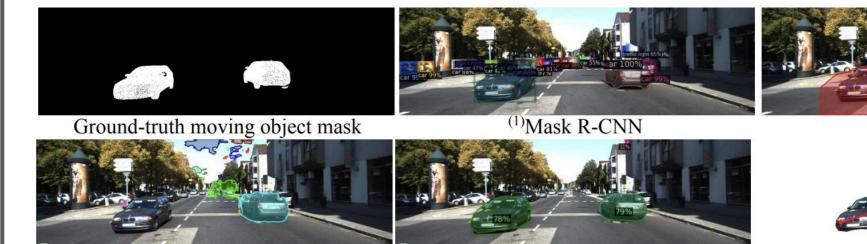
• Collinear motion (ambiguous w/o 1st frame depth Z0)



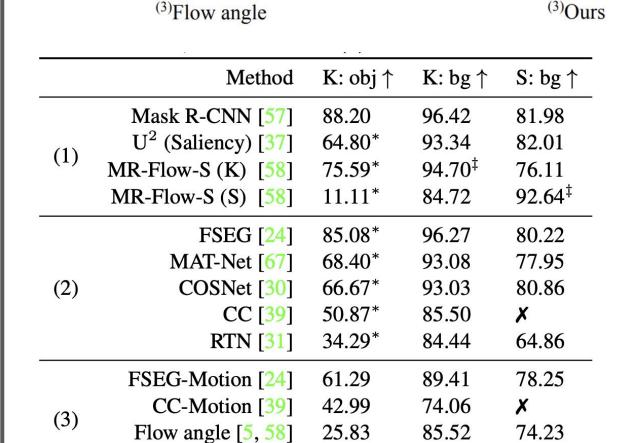
"scale factor to align two depth maps for solving monocular scale ambiguity

Pipeline →Cost Maps and 3D Motion Features In: HxWx(4+8)Out: HxWx(K+1)Rigid Motion Fitting $(\mathbf{R}_0,\mathbf{T}_0),\ (\mathbf{R}_1,\mathbf{T}_1),\ldots(\mathbf{R}_N,\mathbf{T}_N)$ $(\hat{\mathbf{R}}_0, \hat{\mathbf{T}}_0)$ — Rigid Motion Network 2) Rigidity Estimation 1) Initialization 3) Rigid Body Scene Flow Losses $L = L_{ m binary} + L_{ m center} + L_{ m polar}$ Ground-truth Ground-truth Ground-truth foreground mask object contours object centers





97.05



Ours **90.71**

Our rigid motion estimation **Stereo scene flow**

Method	D1* ↓	D2 ↓	Fl↓	SF↓
PRSM [54]	4.27	6.79	6.68	8.97
OpticalExp [63]	1.81	4.25	6.30	8.12
DRISF [32]	2.55	4.04	4.73	6.31
Ours Mask R-CNN	1.89	3.42	4.26	5.61
Ours Rigid Mask	1.89	3.23	3.50	4.89

Ablation study

Method	K: obj↑	K: bg↑	S: bg ↑
Reference	89.53	97.22	84.63
(1) w/o cost maps	88.66	96.59	76.81
(2) w/o uncertainty	85.09	95.72	77.25
(3) w/o monocular depth	84.46	94.84	76.14
(4) w/o expansion (MoA [6])	81.28	95.50	77.00
(5) w/o learning [5, 58]	25.83	85.52	74.23

 $^{(2)}CC$