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Multiframe Scene Flow with Piecewise Rigid Motion

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Scene Flow Estimation:

- input: image sequence (RGB or RGB-D)
- output: 3D displacement field between underlying 3D scene states



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Overview

input RGB-D frames (overlayed) ground truth optical flow

oversegmentation of the reference frame

segmentation transfer into the current frame

our MSF result (projected)

Overview



Vogel et al. ICCV, 2013.



Quiroga et al. ECCV, 2014.



Jaimez et al. ICRA, 2015.



Jaimez et al. 3DV, 2015.

C. Vogel *et al.* Piecewise rigid scene flow. In ICCV, 2013.
J. Quiroga *et al.* Dense semi-rigid scene flow estimation from RGBD images. In ECCV, 2014.
M. Jaimez *et al.* A primal-dual framework for real-time dense rgb-d scene flow. In ICRA, 2015.
M. Jaimez *et al.* Motion cooperation: Smooth piece-wise rigid scene flow from rgb-d images. In 3DV, 2015.





- depth channel is used to obtain oversegmentation of the scene
- segmentation of a scene is kept **fixed**
- a global scene-flow formulation over **multiple frames**



- take advantage of **point set registration** (**projective point-to-plane ICP term**)
- lifting function for coherent segment transformations

$$\begin{split} \mathfrak{E}(\mathbf{T}^{1}, \mathbf{T}^{2}, \dots, \mathbf{T}^{|\mathbf{Z}|}, \mathbf{w}) &= \sum_{\zeta \in \mathbf{Z}} \alpha_{\zeta} \, \mathfrak{E}_{data}(\mathbf{T}^{\zeta}) + \\ &+ \sum_{\zeta \in \mathbf{Z}} \beta_{\zeta} \, \mathfrak{E}_{pICP}(\mathbf{T}^{\zeta}) \, + \, \sum_{\zeta \in \mathbf{Z}} \gamma_{\zeta} \, \mathfrak{E}_{l.reg.}(\mathbf{T}^{\zeta}, \mathbf{w}) + \\ &+ \eta \, \mathfrak{E}_{r.opt.}(\mathbf{w}) + \, \sum_{\zeta = 3}^{|\mathbf{Z}|} \lambda_{\zeta} \, \mathfrak{E}_{c.}(\mathbf{T}^{\zeta}). \end{split}$$

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vector of frame-to-frame segment transformations

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a pyramid with visualized normals



result of pICP

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compute oversegmentation

build a connectivity graph

Laplace

oversegmentation

segment connectivity ²³









compute oversegmentation

build a connectivity graph

Laplace



oversegmentation

segment connectivity ²⁴







compute oversegmentation

build a connectivity graph





segment connectivity ²⁵

Laplace

oversegmentation





lifting function
$$\mathscr{F}(\cdot,\mathbf{w}) = \sum (w_i^2(\cdot) + (1-w_i^2))$$









optimization over multiple frames



Huber norm:

$$\|a^2\|_{\epsilon} = \begin{cases} \frac{1}{2}a^2, & \text{for } |a| \le \epsilon \\ \epsilon(|a| - \frac{1}{2}\epsilon), & \text{otherwise,} \end{cases}$$

In the experimental evaluation we use:

- MPI SINTEL [1]
- virtual KITTI [2]
- Bonn multibody data set [3]
- own RGB-D recordings

- ... and compare the following methods:
- Primal-Dual Flow [4]
- Semi-Rigid Scene Flow [5]
- Multi-Frame Optical FLow [6]
- tv-l1 optical flow [7]

[1] D. J. Butler *et al.* A naturalistic open source movie for optical flow evaluation. In ECCV, 2012.
[2] A. Gaidon *et al.* Virtual worlds as proxy for multi-object tracking analysis. In CVPR, 2016.
[3] J. Stueckler and S. Behnke. Efficient dense rigid-body motion segmentation and estimation in rgb-d video. IJCV, 2015.

[4] M. Jaimez *et al.* A primal-dual framework for real-time dense rgb-d scene flow. In ICRA, 2015.

[5] J. Quiroga et al. Dense semi-rigid scene flow estimation from RGBD images. In ECCV, 2014.

[6] B. Taetz et al. Occlusion-aware video registration for highly non-rigid objects. In WACV, 2016.

[7] C. Zach *et al.* A duality based approach for realtime tv-l1 optical flow. In GCPR, 2007.

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```
End Point Error is defined as \|(u - u_{\text{GT}}), (v - v_{\text{GT}})\|
(u, v)^{\mathsf{T}} is a projected flow vector
(u_{\text{GT}}, v_{\text{GT}})^{\mathsf{T}} is a ground truth vector
```

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	alley1	bandage1	sleeping2, rigid
SRSF [5]	2.46122/2.40833	2.47801/2.46389	1.13584
MSF	0.740127	1.69865	0.307526

...



Conclusions and Future Work



We propose a new multiframe RGB-D scene flow approach

Main novelties:

- segmentation is obtained on the depth channel and kept fixed
- projective ICP term
- lifted segment pose regularizer

Next: combine MSF with semantic segmentation, test other energy terms



Thank you for your attention!

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