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European Conference on Computer Vision

Dense Semi-Rigid Scene Flow Estimation from RGBD images

Julián Quiroga, Thomas Brox, Frédéric Devernay, James Crowley




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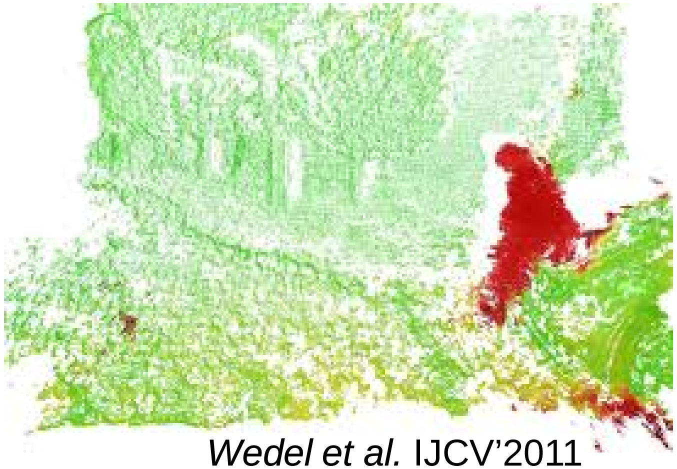
Pontificia Universidad JAVERIANA

Motivation

The **scene flow** is the 3D motion field of the scene (*Vedula et al.* ICCV'99).



Wedel et al. IJCV'2011

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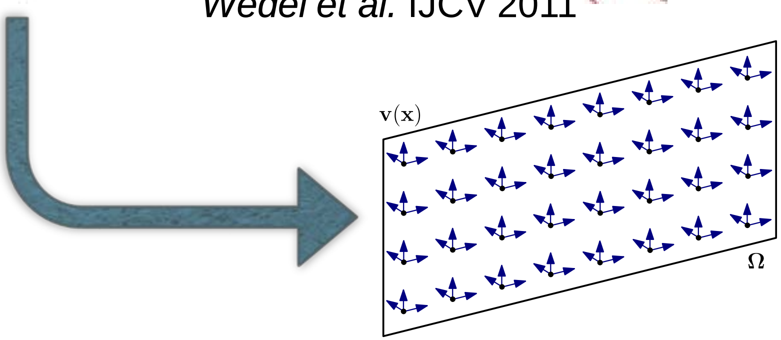

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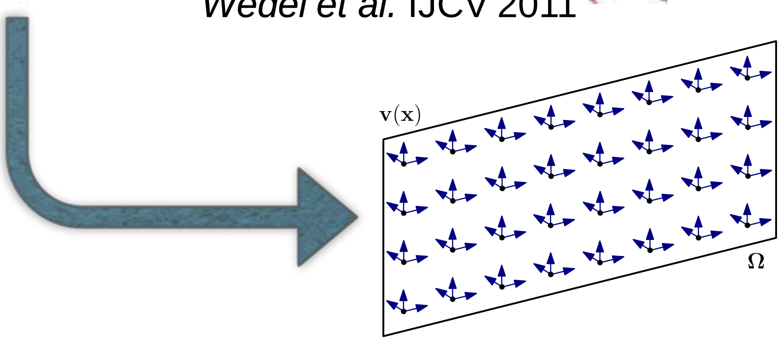

Applications:

- 3D motion capture
- 3D modeling on non-rigid objects
- Autonomous navigation
- Interaction
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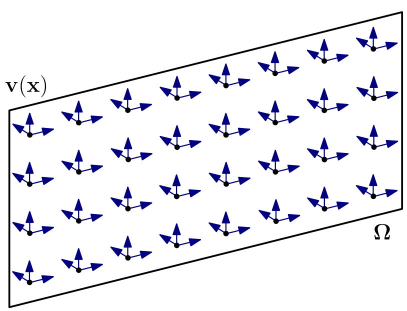

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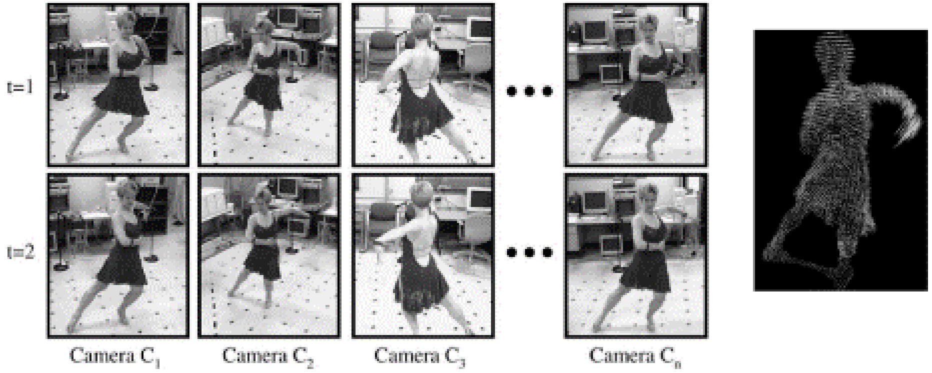
Estimation:

- Unknown 3D structure
- Given the 3D structure

Scene Flow Estimation

from stereo or multi-view

✪ Computing several optical flows (*Vedula et al.* PAMI'05):



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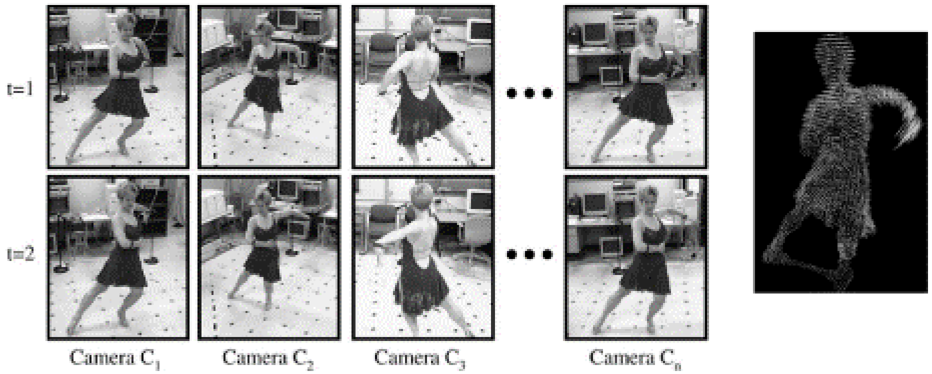

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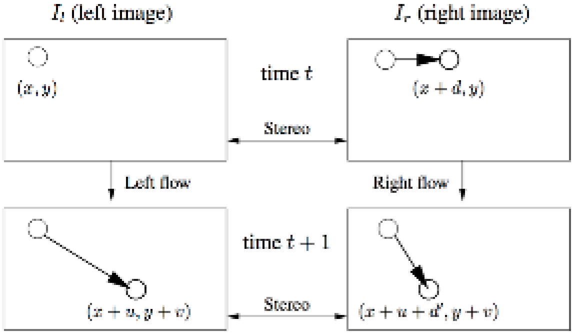

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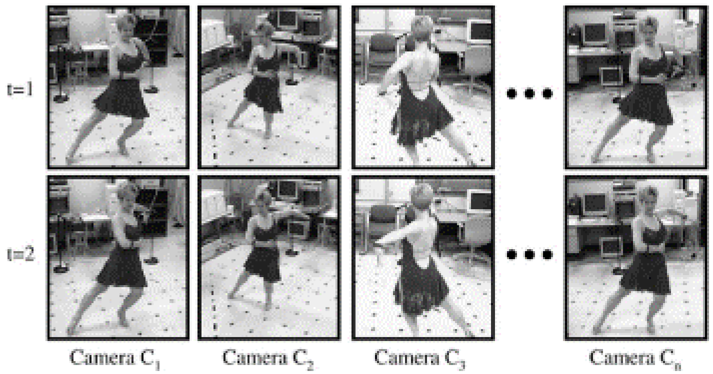

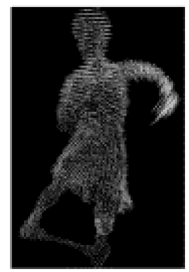

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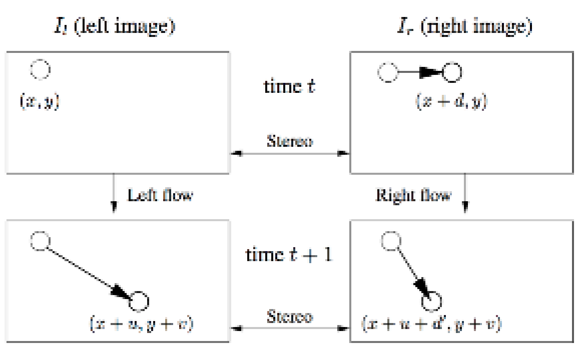

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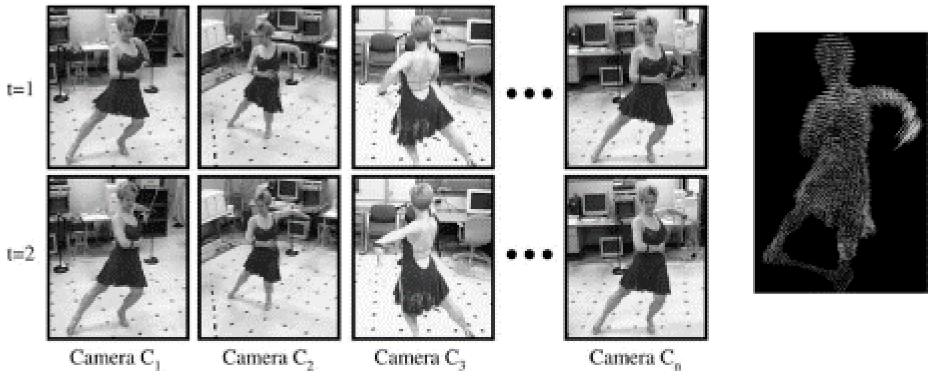

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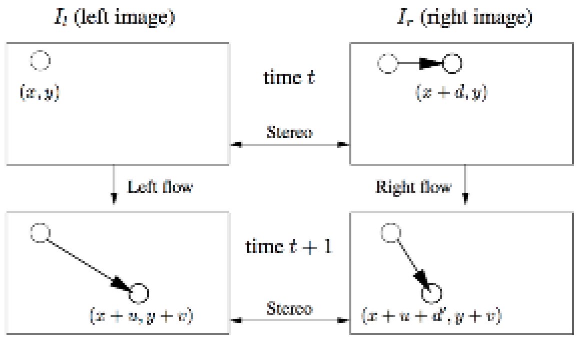

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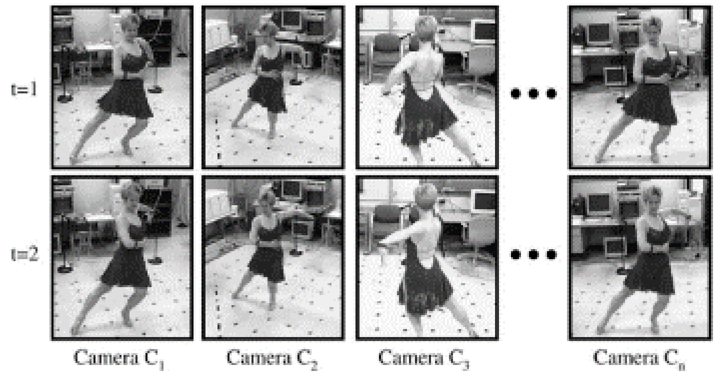

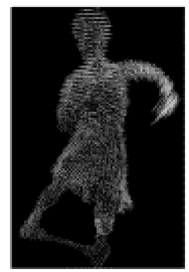

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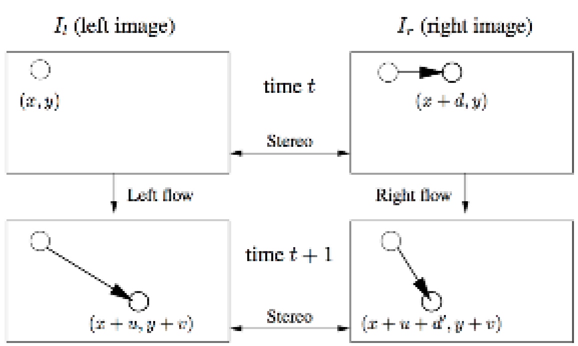
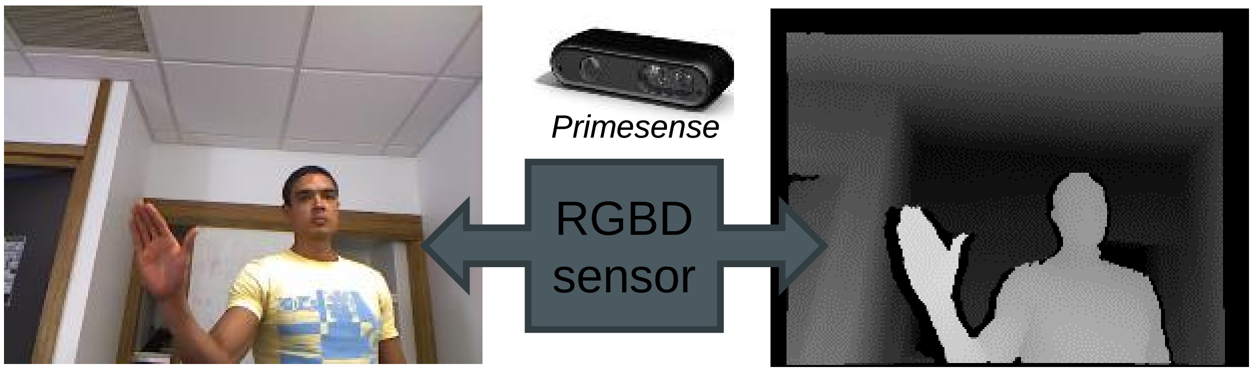


If a **depth sensor** is available?

RGBD data

✪ ***RGBD image:*** a registered pair of color and depth images



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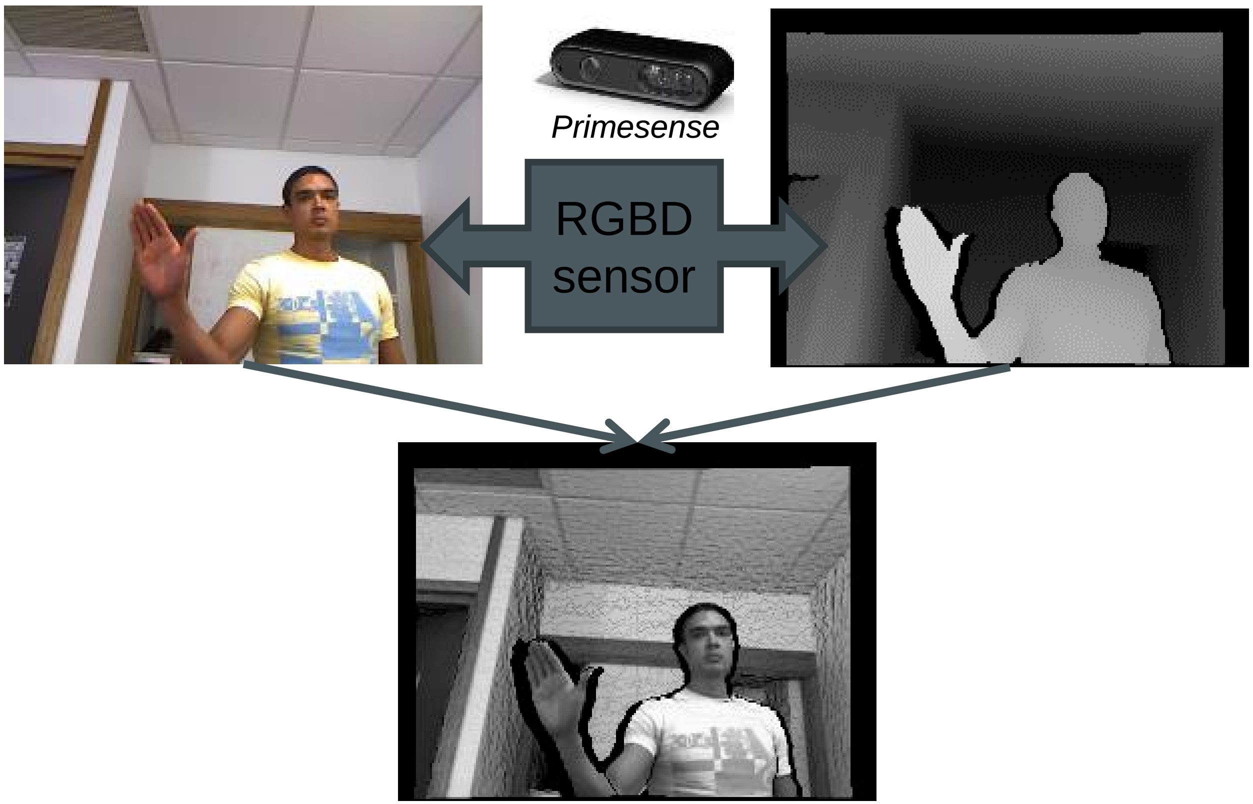

RGBD representation of the scene

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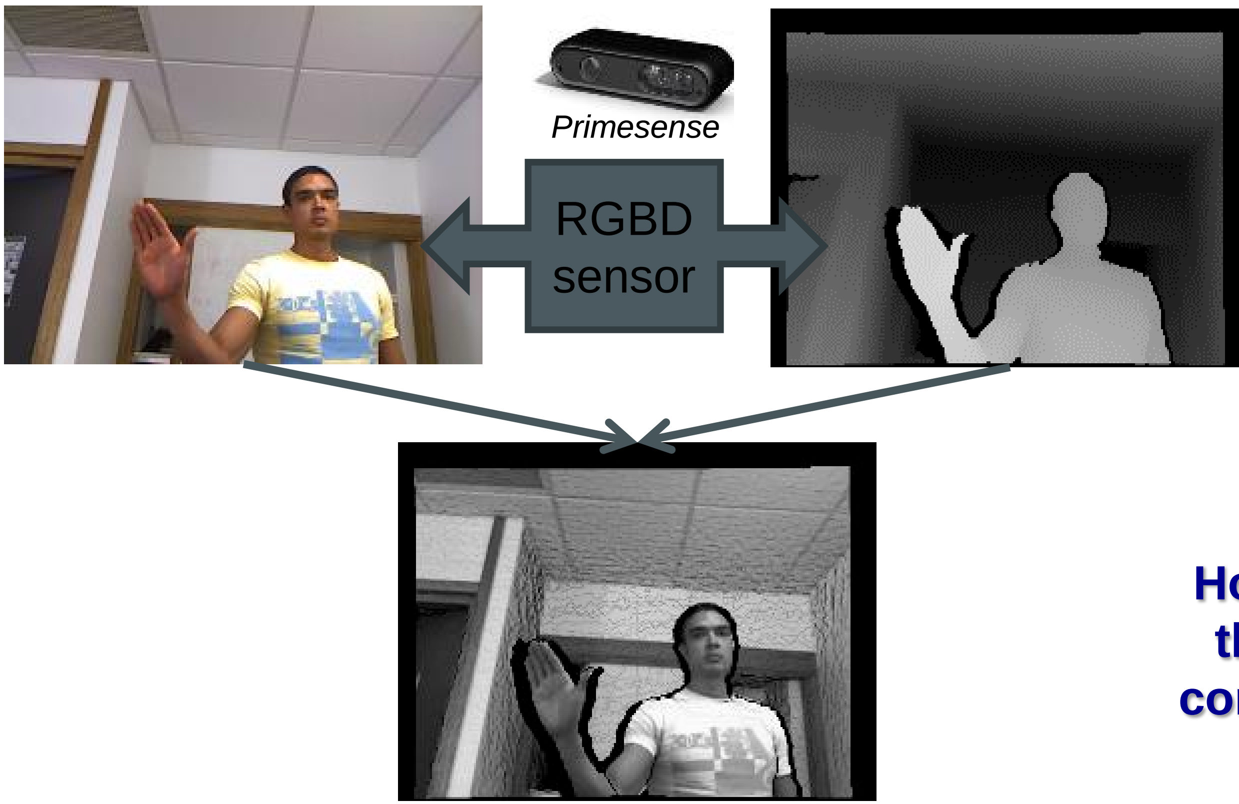

RGBD representation of the scene

How to fully exploit the RGBD data to compute a confident scene flow?

Scene Flow Estimation

from RGBD images

- Using RGB data as an additional channel (*Spies et al.* CVIU'02, *Lukins et al.* BMVC'04):

$$0 = I_x u + I_y v + I_t$$

Optical flow equation

$$w = Z_x u + Z_y v + Z_t$$

Range flow equation

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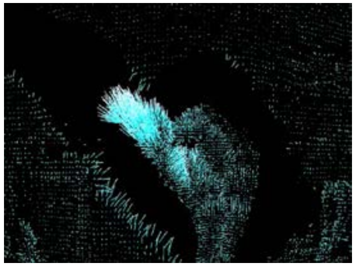

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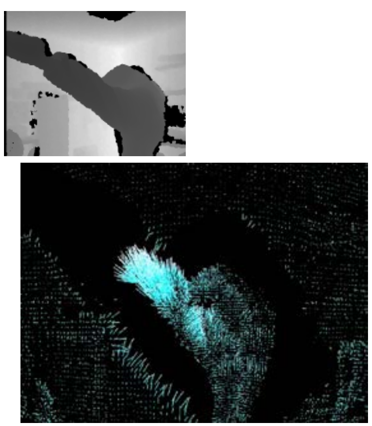
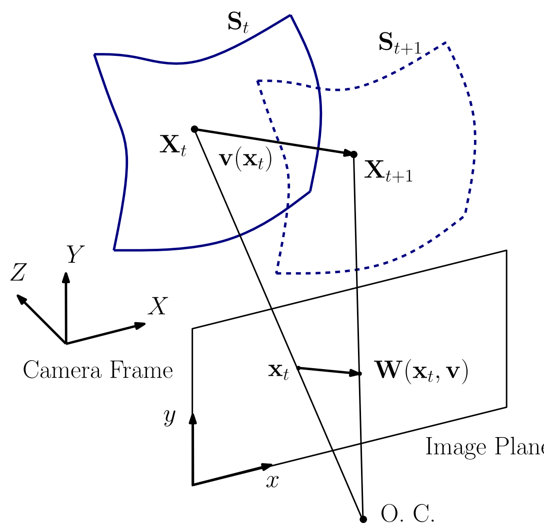


- Projective warping function

(*Quiroga et al*. CVPRW'12 ,ICIP'13)



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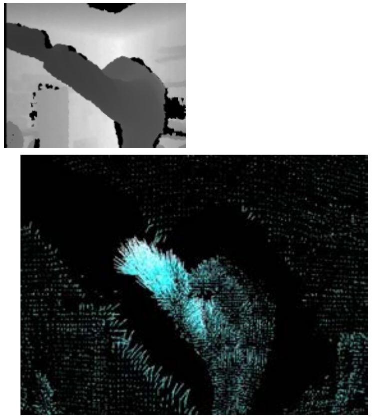

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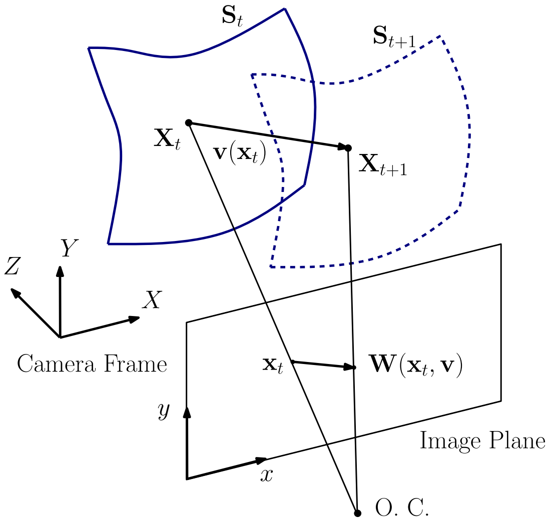
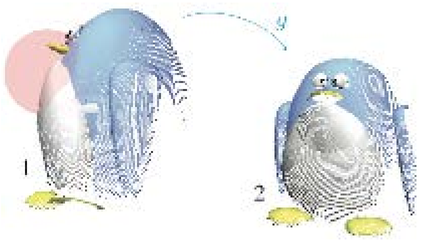


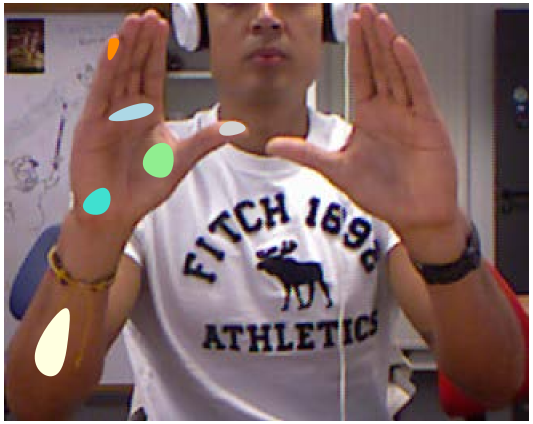
- Matching 3D patches

(*Hornacek et al. CVPR*'14)



Proposed approach

- ***Idea:*** Exploit the semi-rigidity of real-world scenes



Local rigidity

Piecewise rigidity

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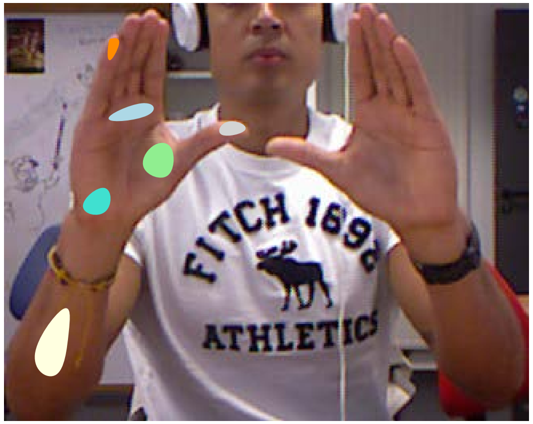

Local rigidity

Piecewise rigidity

How?

Proposed approach (cont.)

- Using an over-parametrization of the 3D motion

$$\xi(\mathbf{x}) : \mathbf{\Omega} \rightarrow \mathbb{R}^6$$

Motion field of rigid motions

Proposed approach (cont.)

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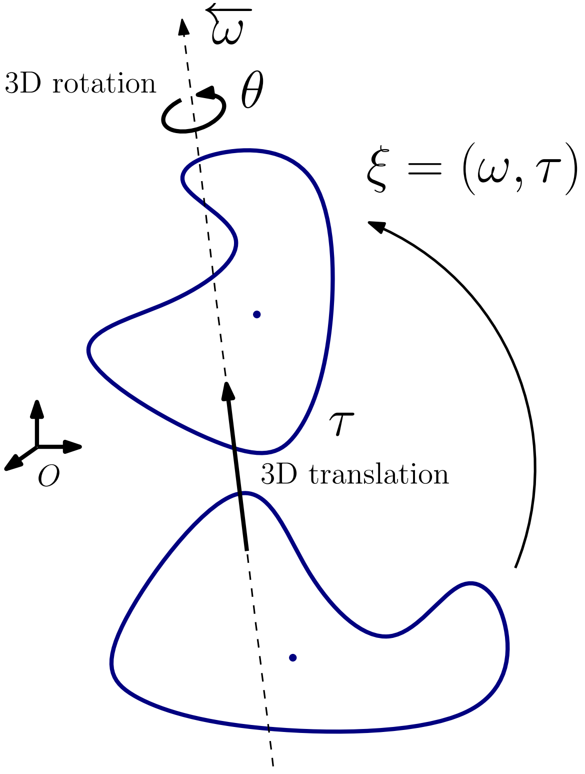
Motion field of rigid motions

*Every scene point follows a **twist motion***



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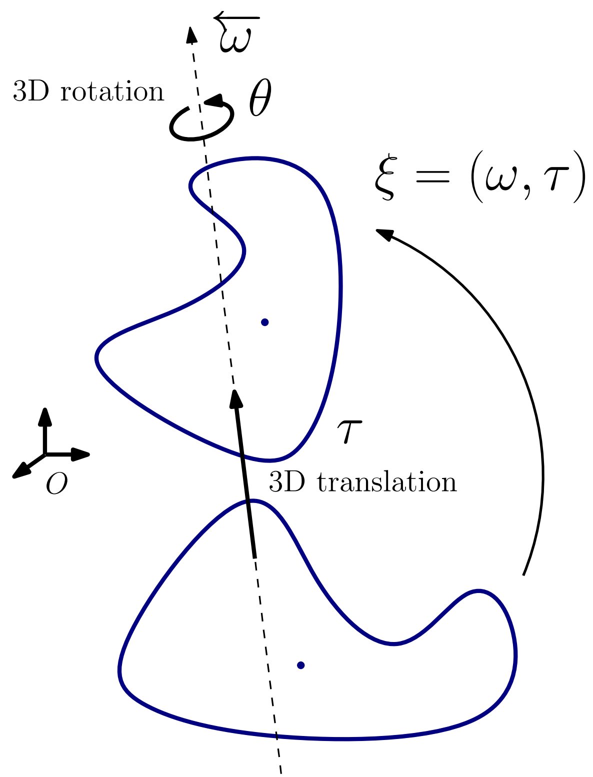

- Scene flow recovery: $\boxed{\tilde{\mathbf{X}}_{t+1} = e^{\hat{\xi}(\mathbf{x}_t)}\tilde{\mathbf{X}}_t}$

Exponential map

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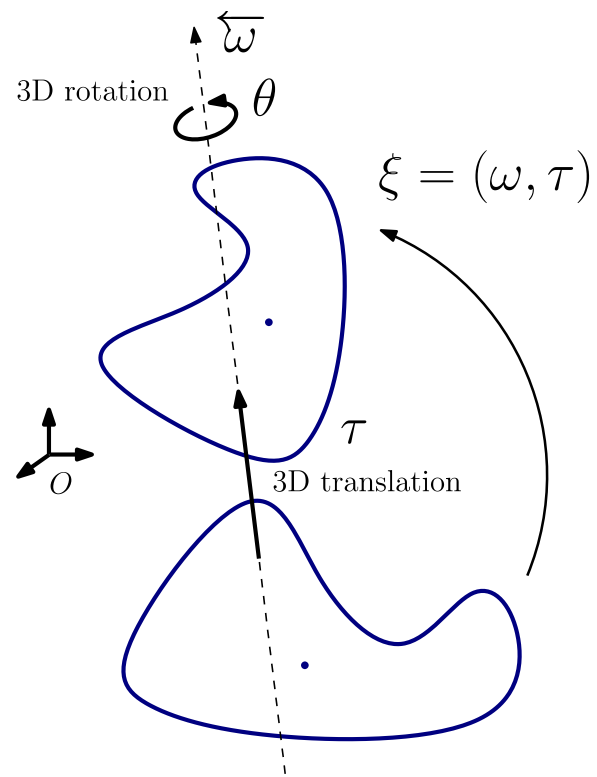

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Exponential map

- We focus on two-frames scene flow estimation

Semi-rigid Scene Flow Energy

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Smoothness term

- Favors **piecewise rigid solutions**
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An adjustable combination of both!

Data term

- **Consistency between motion and RGBD data**

$$\mathbf{x}_{t+1} = \mathbf{W}(\mathbf{x}_t, \xi)$$

Warping function

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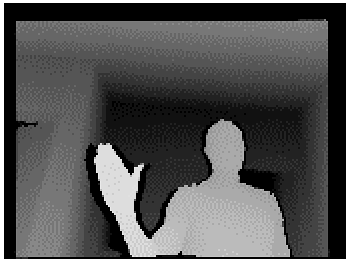
Brightness (I)

Brightness gradient (I_g)



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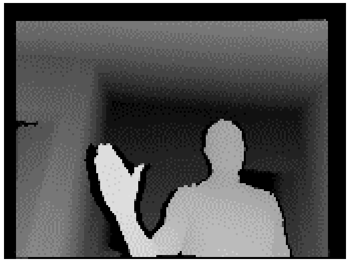

Depth (Z)

$$\rho_{data}(\mathbf{x}, \xi) = \Psi\left(\rho_I^2(\mathbf{x}, \xi) + \gamma\rho_g^2(\mathbf{x}, \xi)\right) + \lambda\Psi\left(\rho_Z^2(\mathbf{x}, \xi)\right)$$

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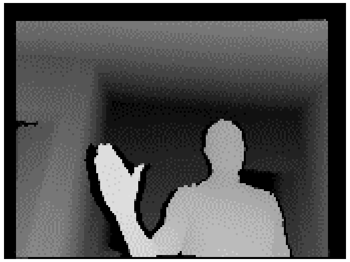

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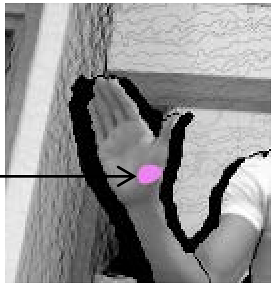

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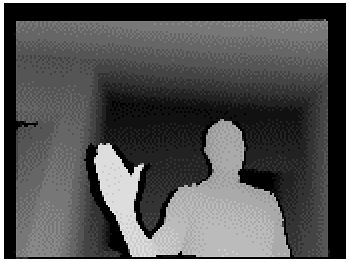

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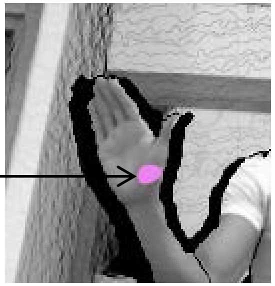

$$\boxed{E_D(\xi) = \sum_{\mathbf{x} \in \boldsymbol{\Omega}} \rho^L(\mathbf{x}, \xi)}$$

Full data term

Smoothness term

- Piecewise rigidity

Total variation (TV) favors
piecewise smooth solutions

Smoothness term

- **Piecewise rigidity**

Total variation (TV) favors piecewise smooth solutions

Decoupling

Translational field

$$\tau : \Omega \to \mathbb{R}^3$$

$$\xi : \Omega \to \mathbb{R}^6$$

$$\omega : \Omega \to \mathbb{R}^3$$

Rotational field

Smoothness term

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Rotational field

$$\mathbf{TV}_c(\tau) = \sum_{\mathbf{x}} c(\mathbf{x}) \, \|\nabla \tau(\mathbf{x})\|$$

Channel-by-channel TV

Smoothness term

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Vectorial TV (Goldluecke et al. SIIMS’12)

Smoothness term

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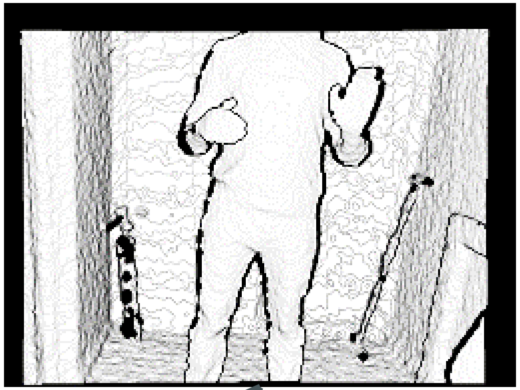

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Optimization

- The energy is minimized using the **variable splitting** method:

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Regularized weighted least-squares

IRLS with a Gauss-Newton algorithm

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Vectorial ROF model

Gradient descent and re-projection on the dual-ROF model

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Alternation

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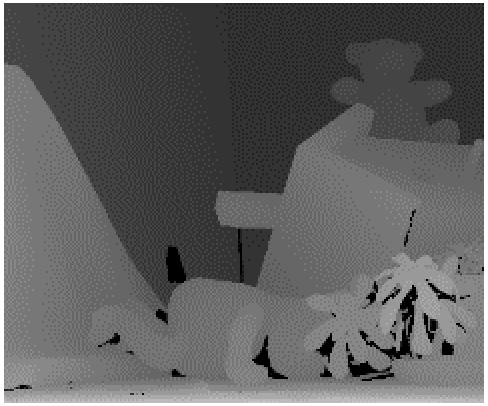
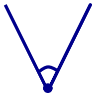
Experiments

Middlebury stereo datasets





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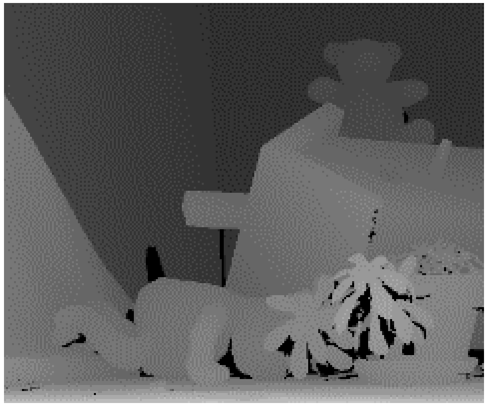

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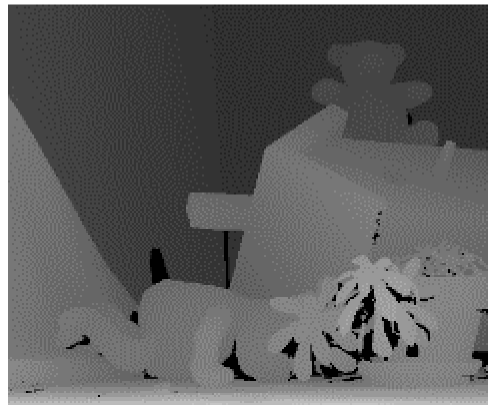

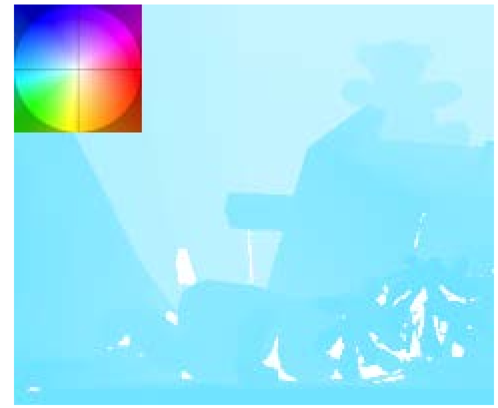

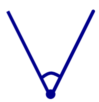

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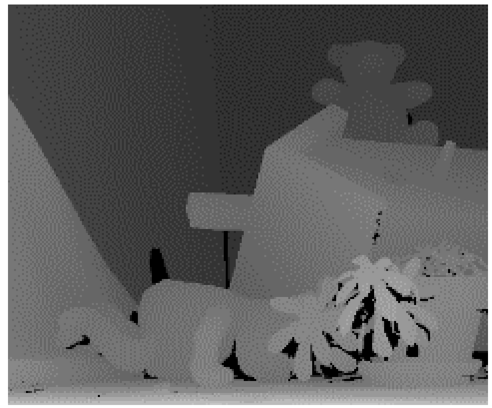
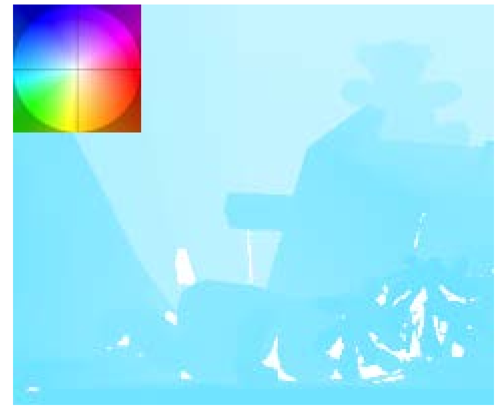
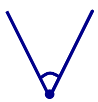
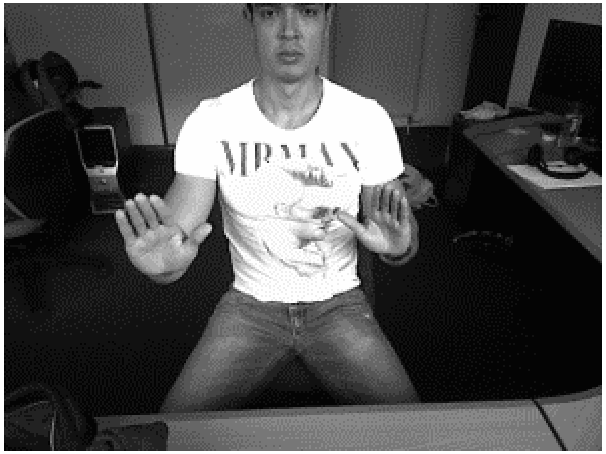
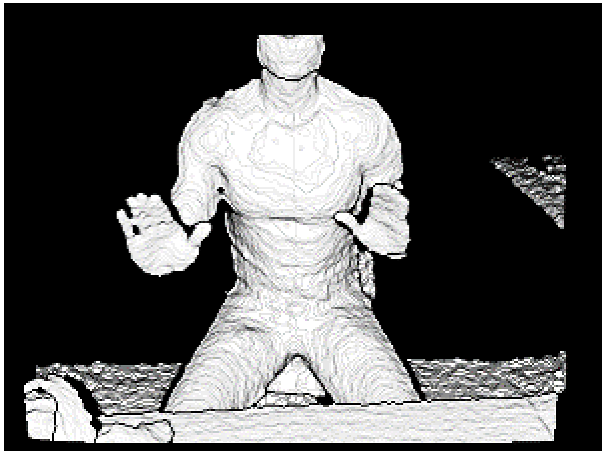




	Views	Teddy		Cones	
		RMS	AAE	RMS	AAE
Semi-rigid Scene Flow (ours)	1	0.49	0.46	0.45	0.37
Hadfield and Bowden [5]	1	0.52	1.36	0.59	1.61
Quiroga *et al.* [13]	1	0.94	0.84	0.79	0.52
Brox and Malik [2] + depth	1	2.11	0.43	2.30	0.52
Basha *et al.* [1]	2	0.57	1.01	0.58	0.39
Huguet and Devernay [8]	2	1.25	0.51	1.10	0.69

Non-rigid motion estimation





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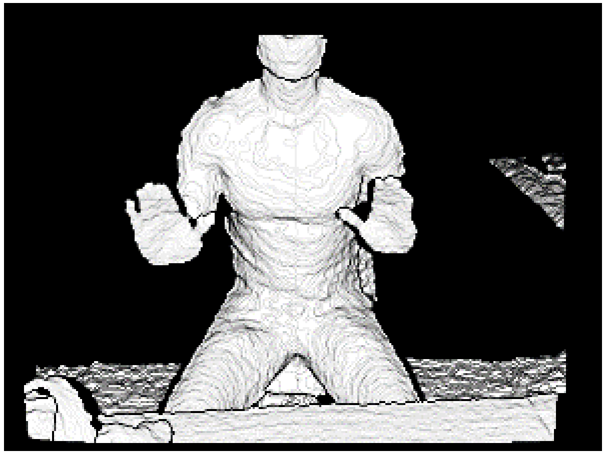

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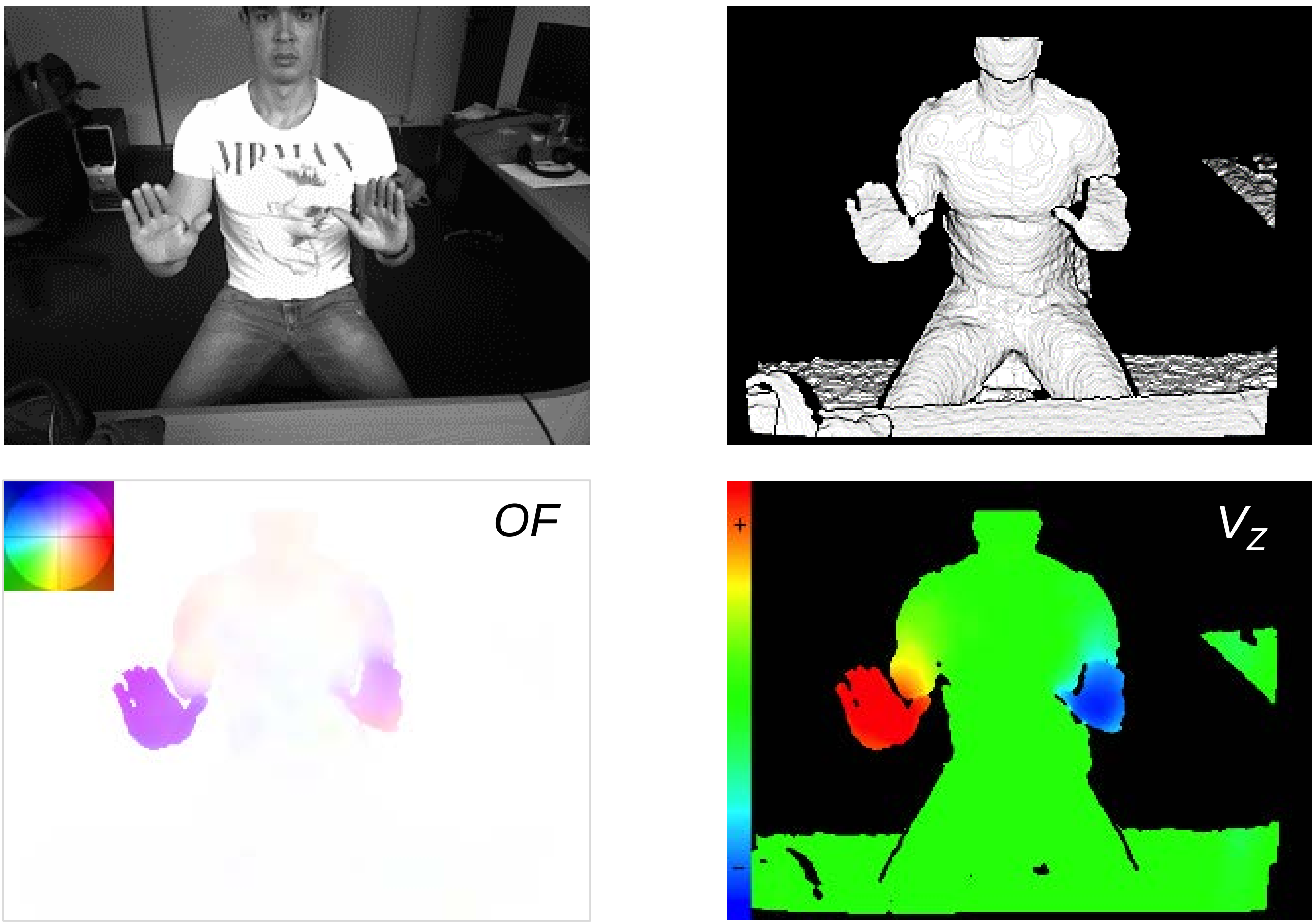
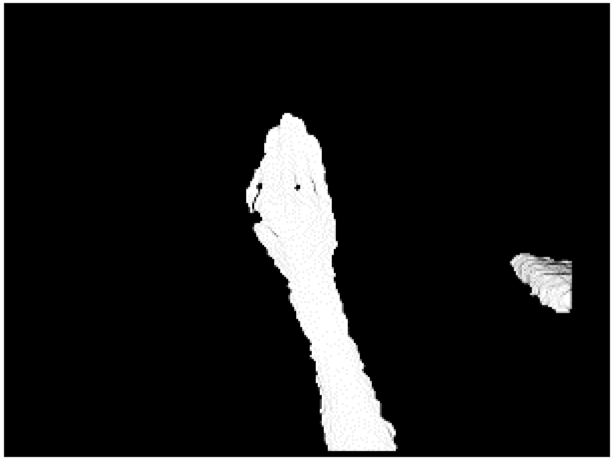
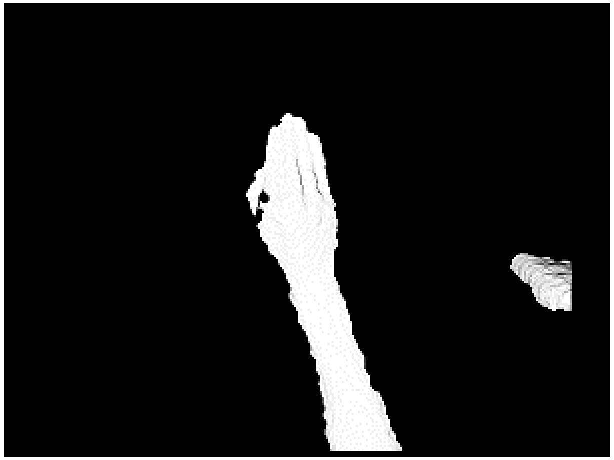


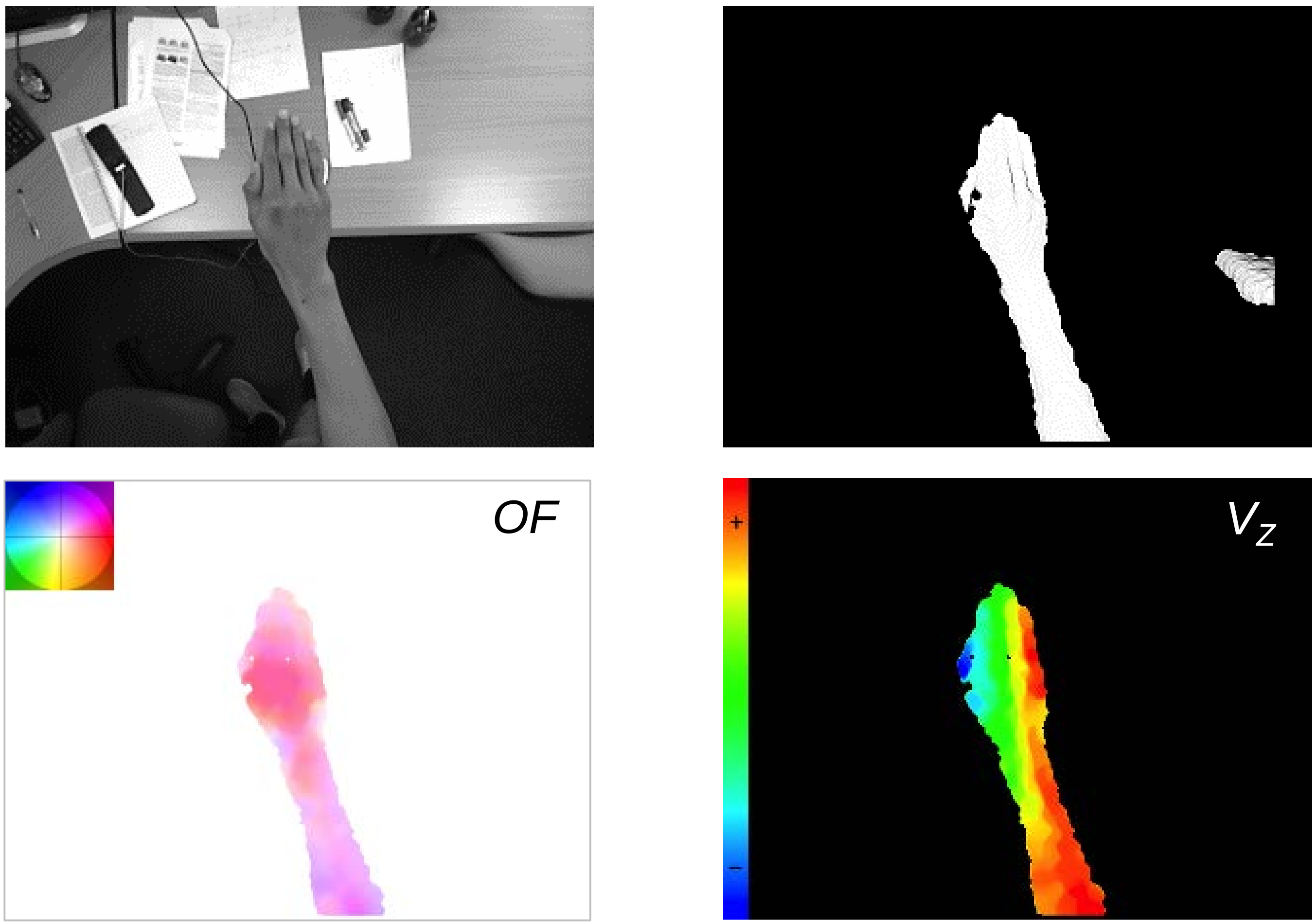
Non-rigid motion estimation (cont.)

Non-rigid motion estimation (cont.)



Non-rigid motion estimation (cont.)



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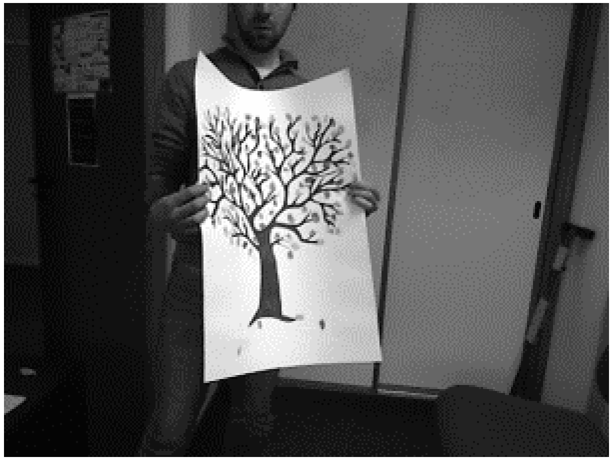

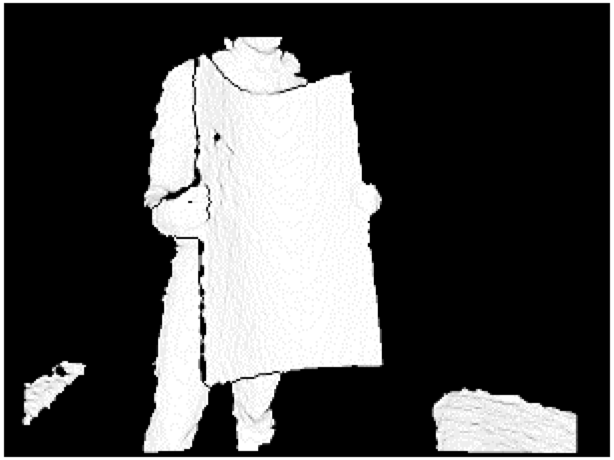

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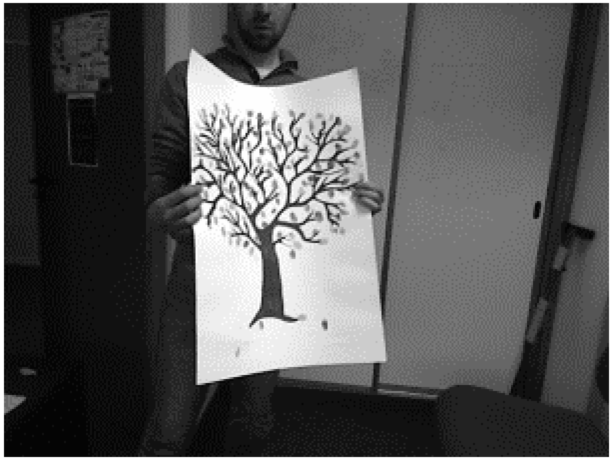

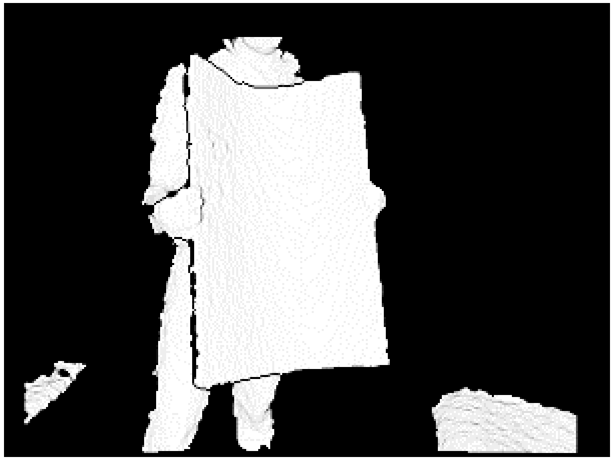

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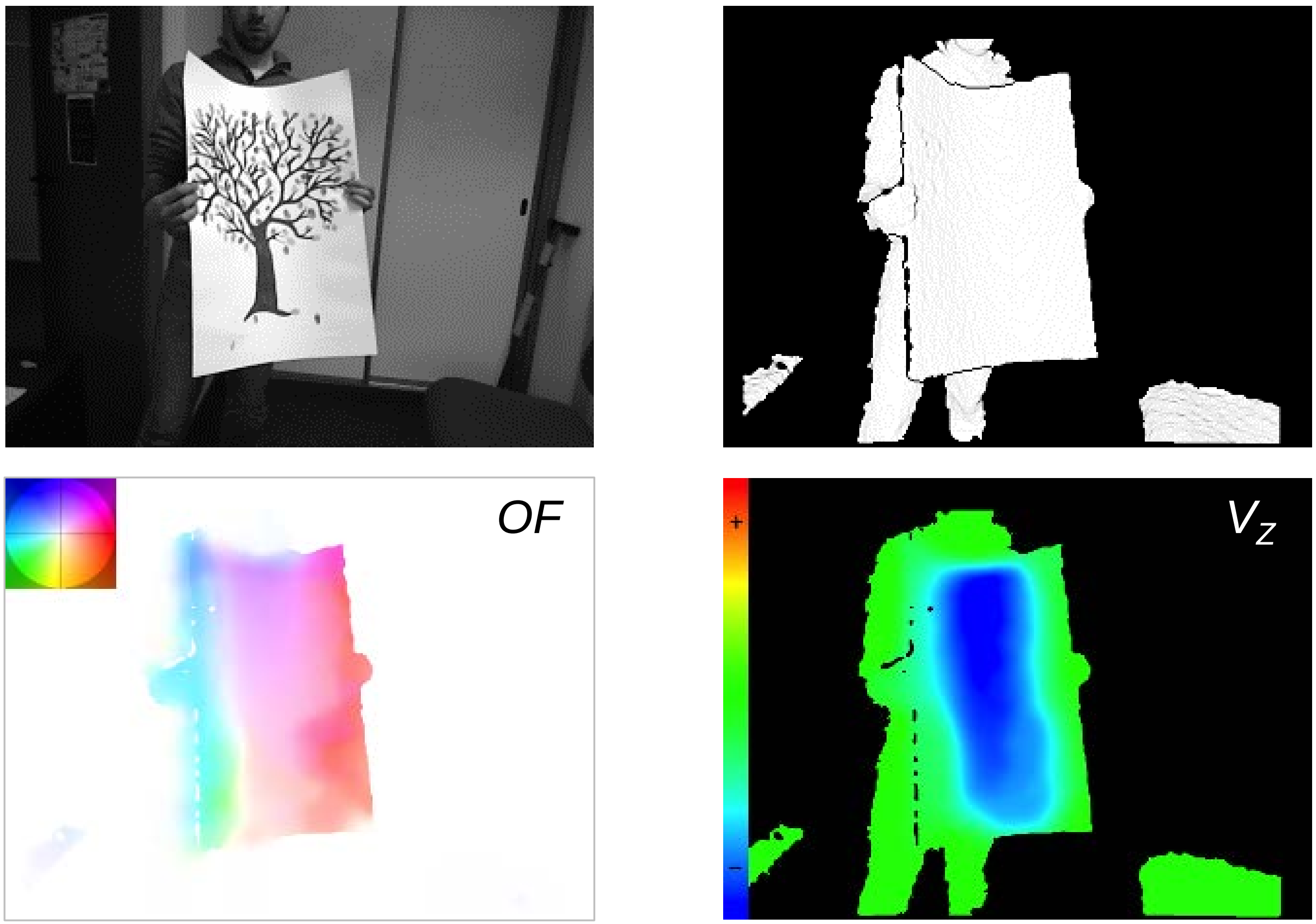

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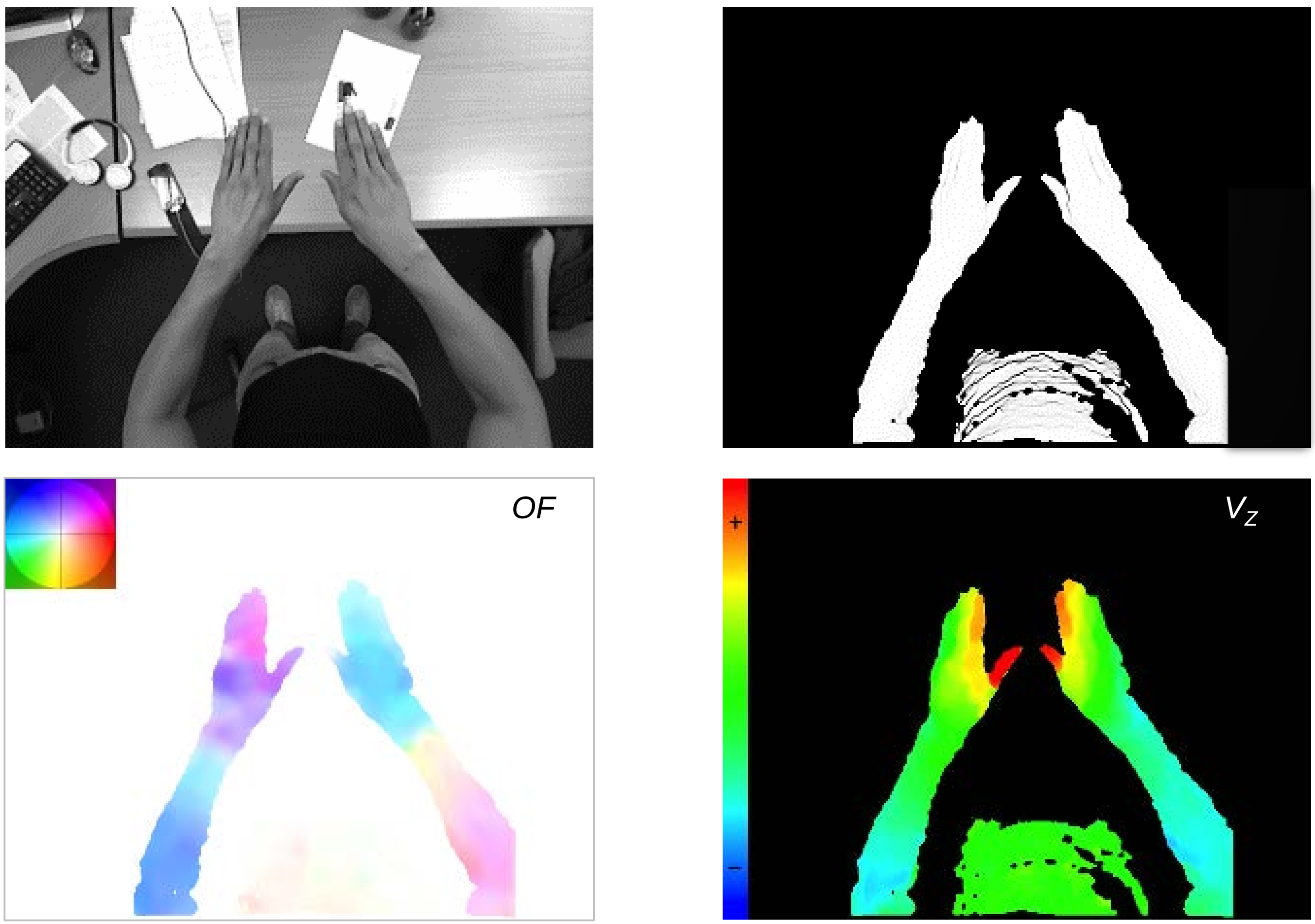

Applications

Rigid motion estimation

- ***A particular case:*** solving for a single twist motion

$$E_{\mathbf{Rig}}(\xi_{\mathrm{R}}) = \sum_{\mathbf{x}\in\mathbf{\Omega}} \rho_{data}\left(\mathbf{x}, \xi_{\mathrm{R}}\right)$$

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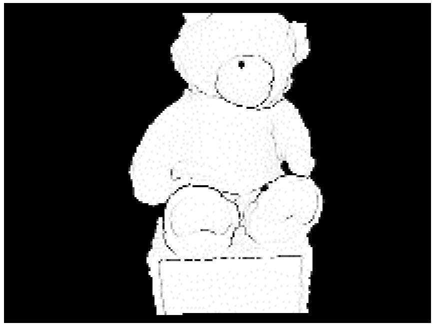

RGBD dataset
(*Sturm et al.* IROS'12)

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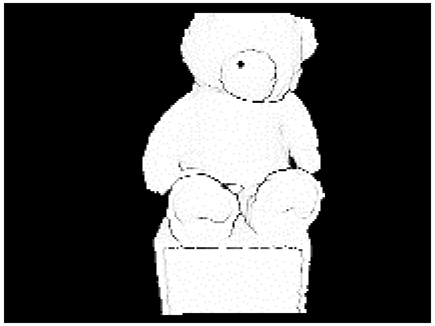

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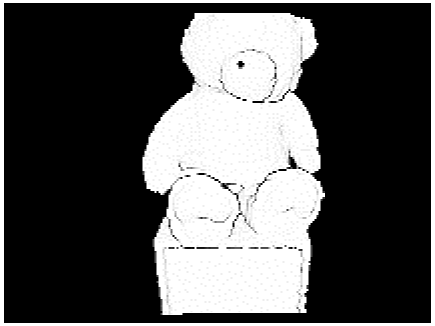

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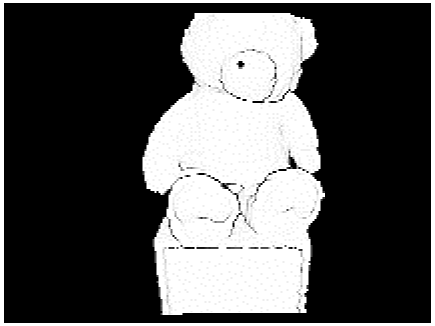

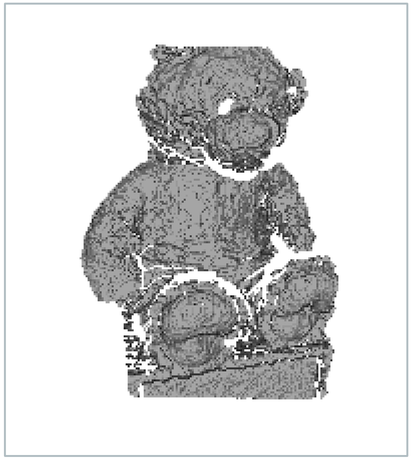

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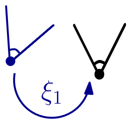

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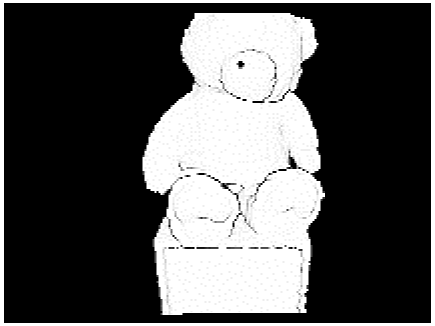

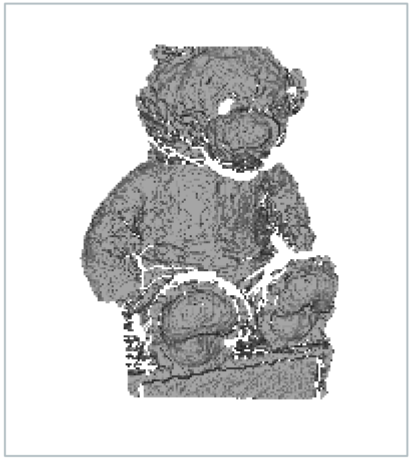

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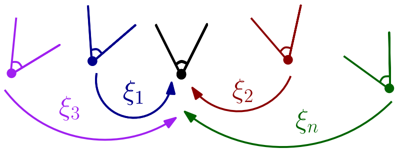

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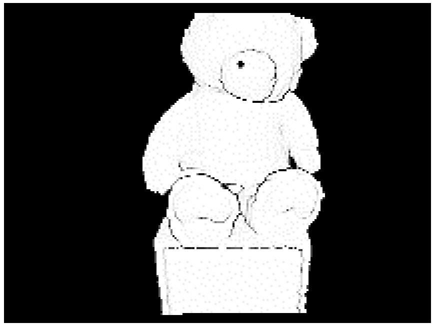

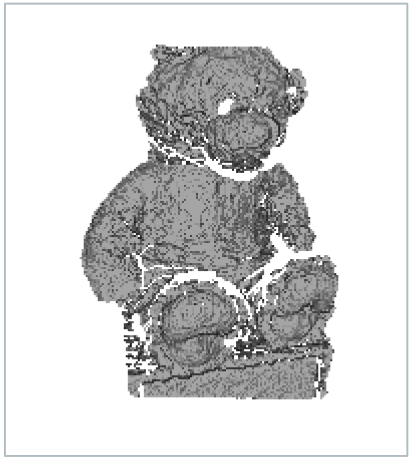

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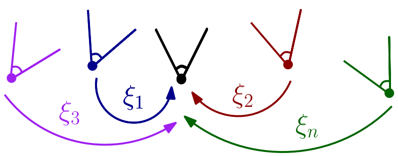

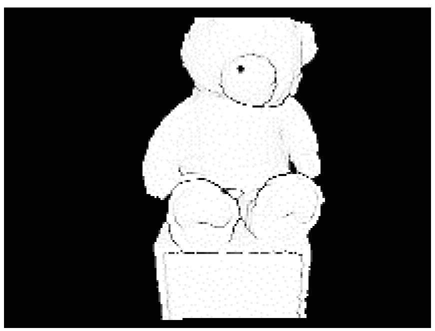

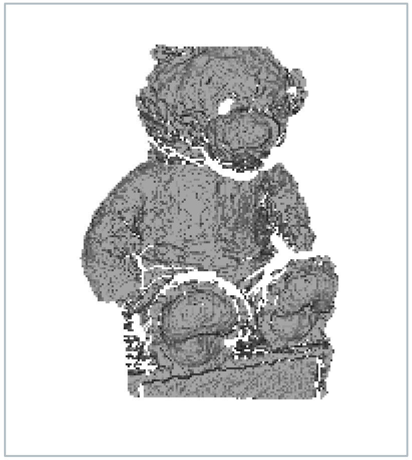

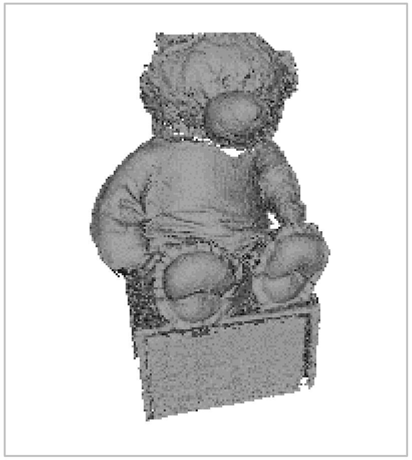

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Scene flow with camera motion estimation

- Knowing the camera motion can simplify the estimation and is useful for applications

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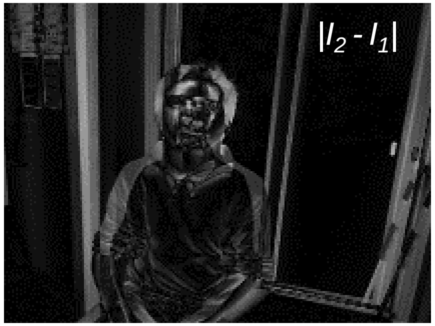

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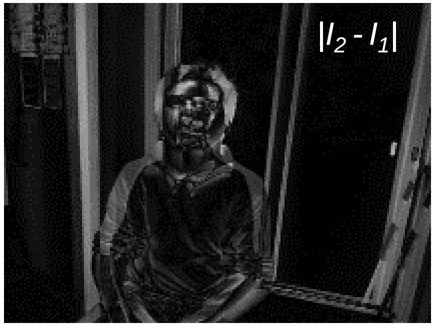

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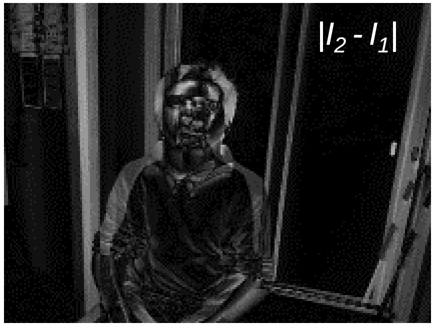

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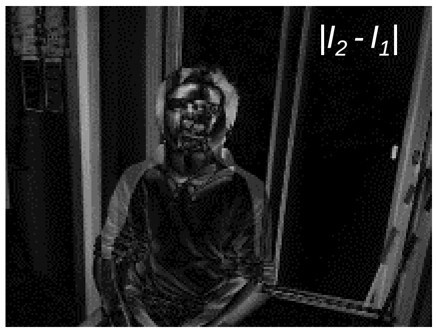

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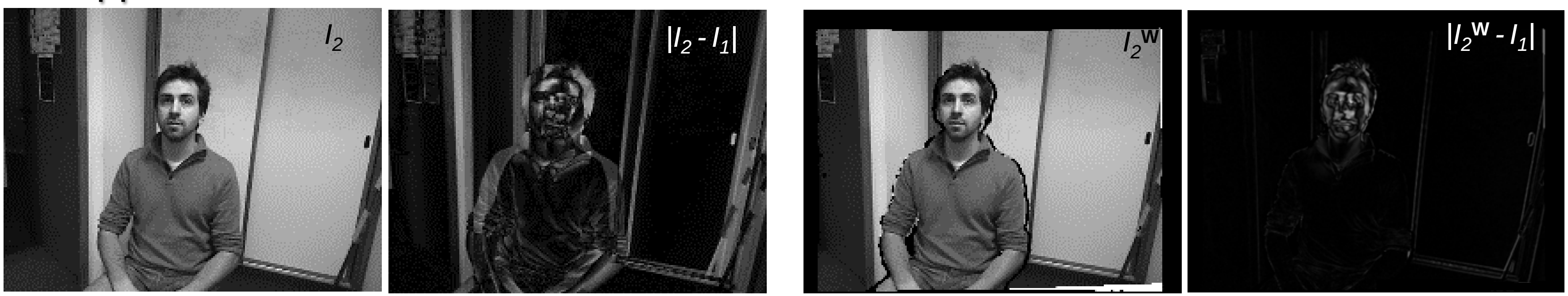

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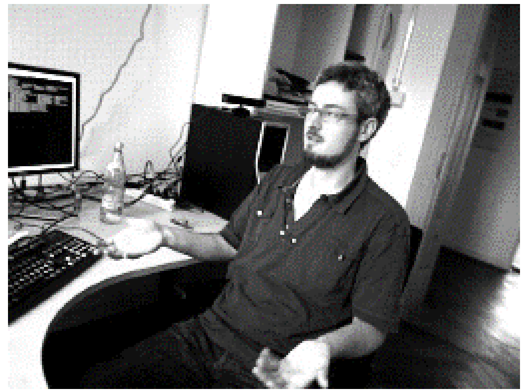
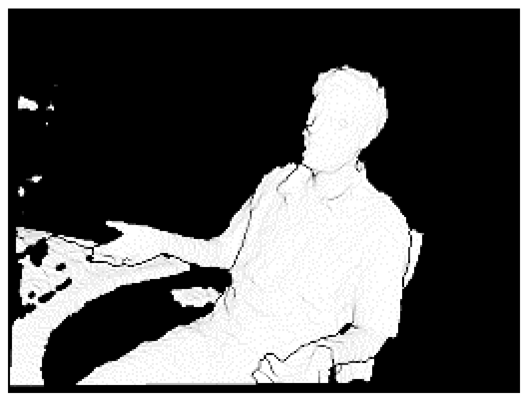
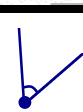
$$\boxed{\min_{\chi} \; E_{\mathbf{Rig}}(\chi) + E_{\mathbf{Res}}(\chi)}$$

Proposed energy

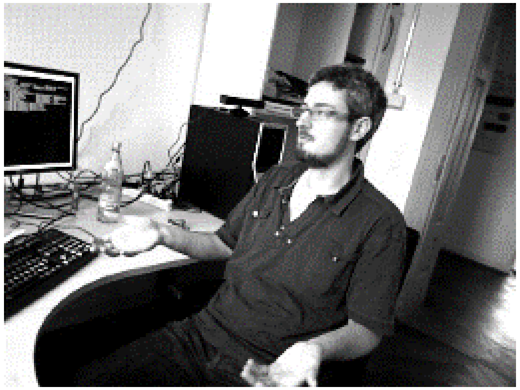
Scene flow with camera motion estimation (cont.)

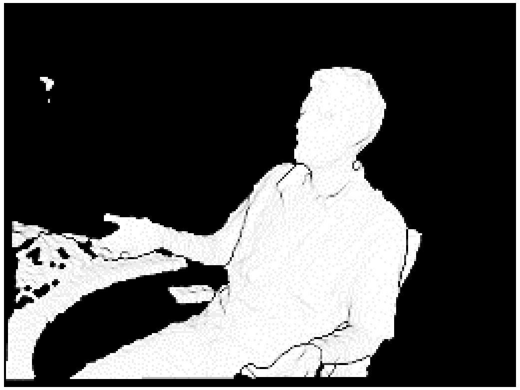


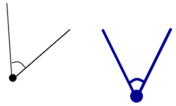




Scene flow with camera motion estimation (cont.)







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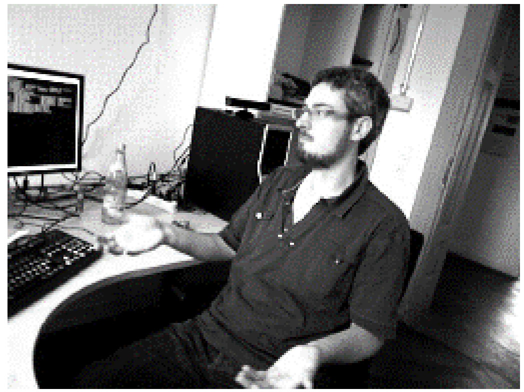

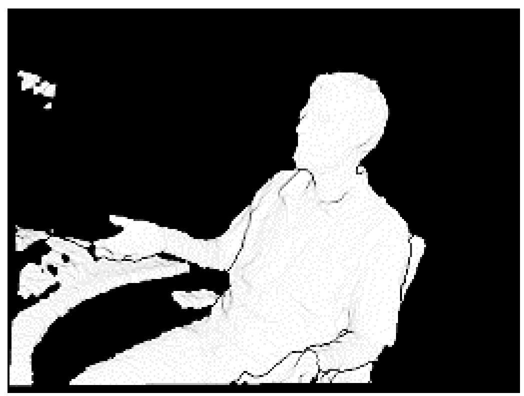

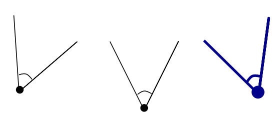

Scene flow with camera motion estimation (cont.)

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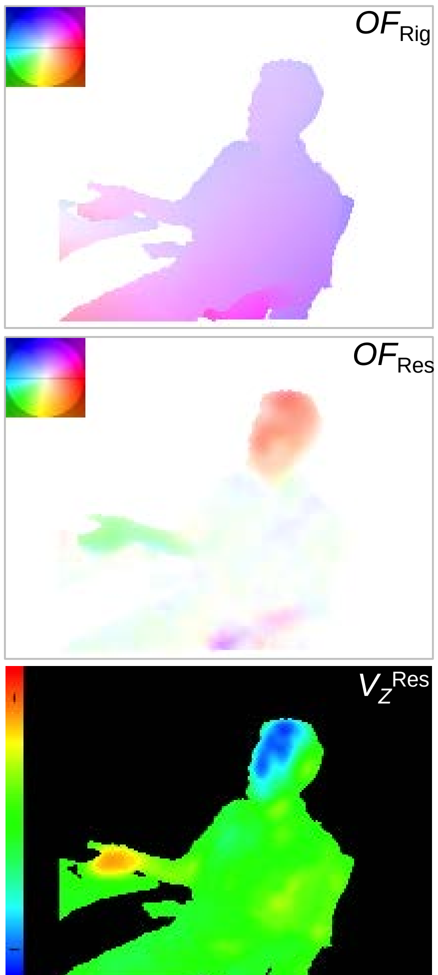
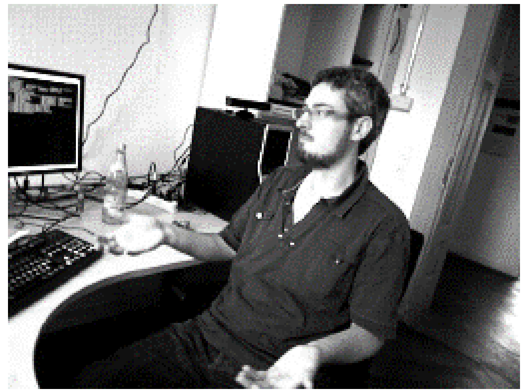
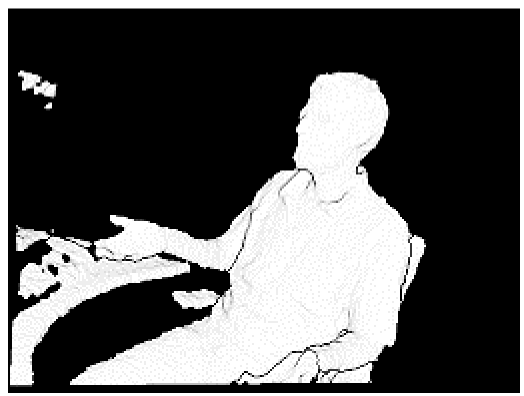
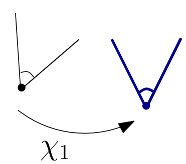
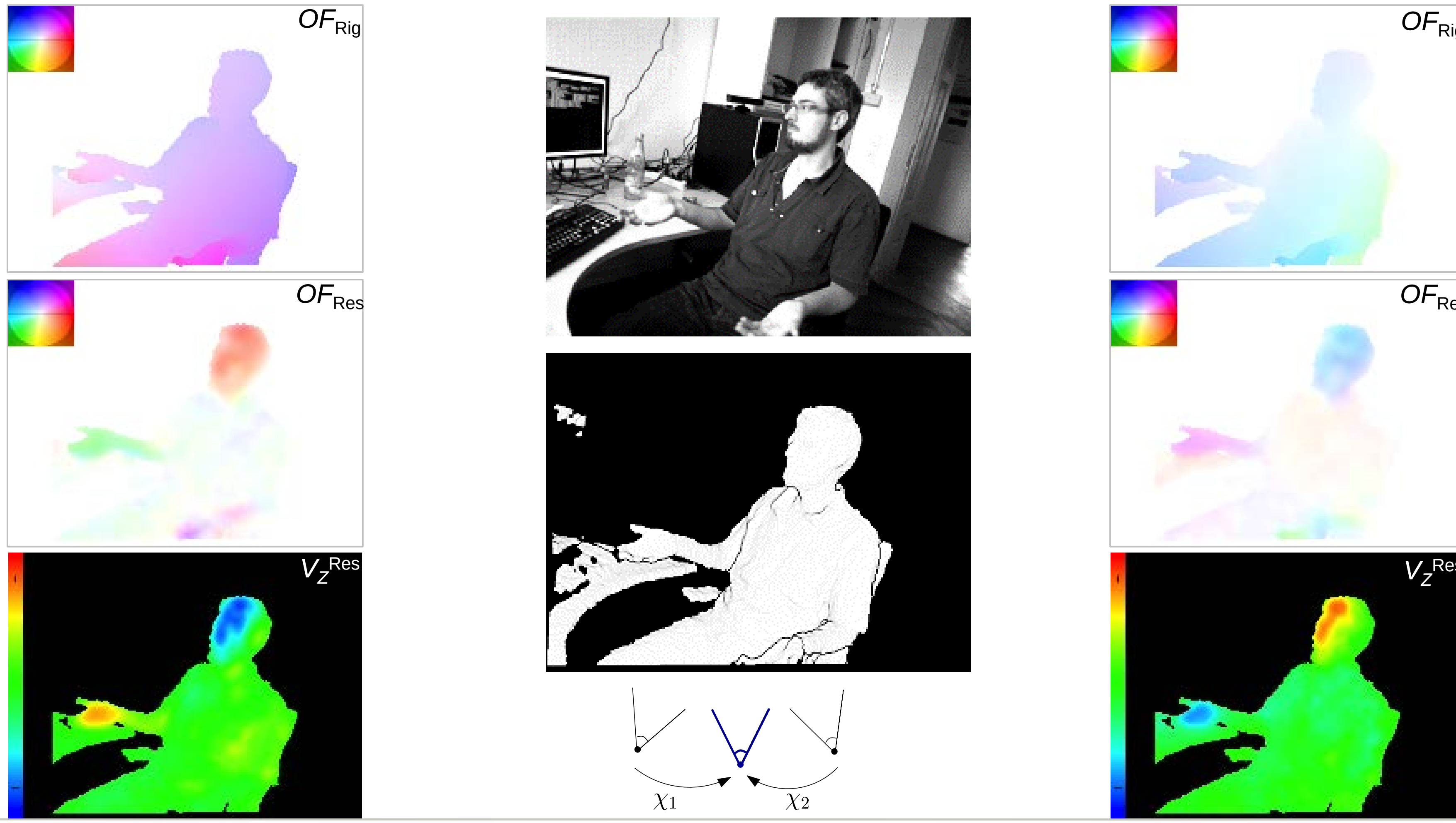








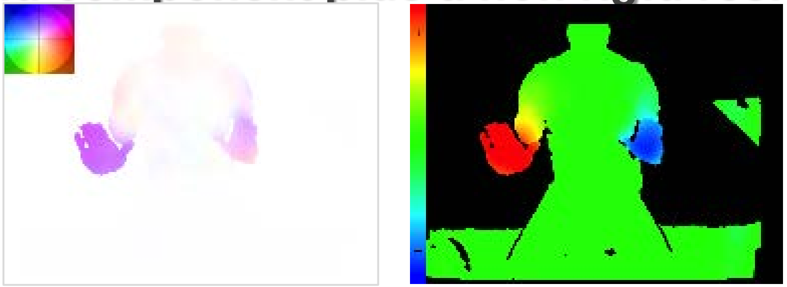
Scene flow with camera motion estimation (cont.)



Conclusion

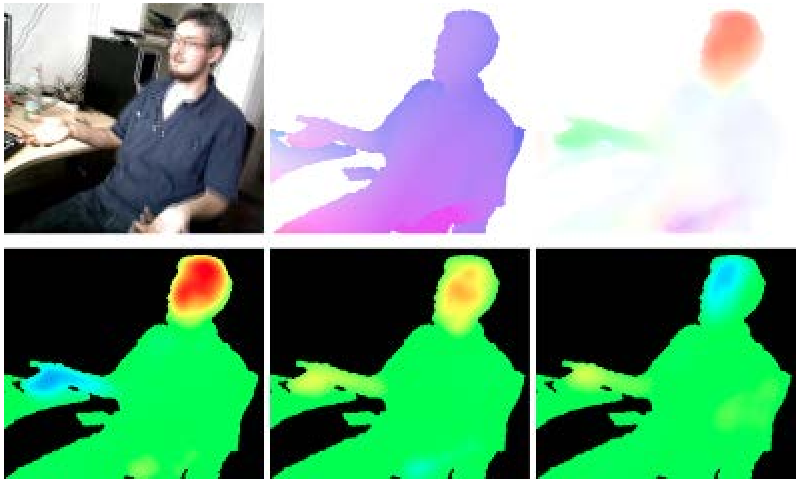
- We have presented a new method to compute a dense scene flow from RGBD images by **modeling the motion as a field of rigid motions**.
- We proposed an **adjustable combination between local and piecewise rigidity**

- We model the motion as a **rigid component plus a non rigid residual**



- **Future work:**
  - Temporal consistency
  - Real-time implementation
  - Large displacements

Thanks!



Semi-rigid scene flow code
will beavailable soon!