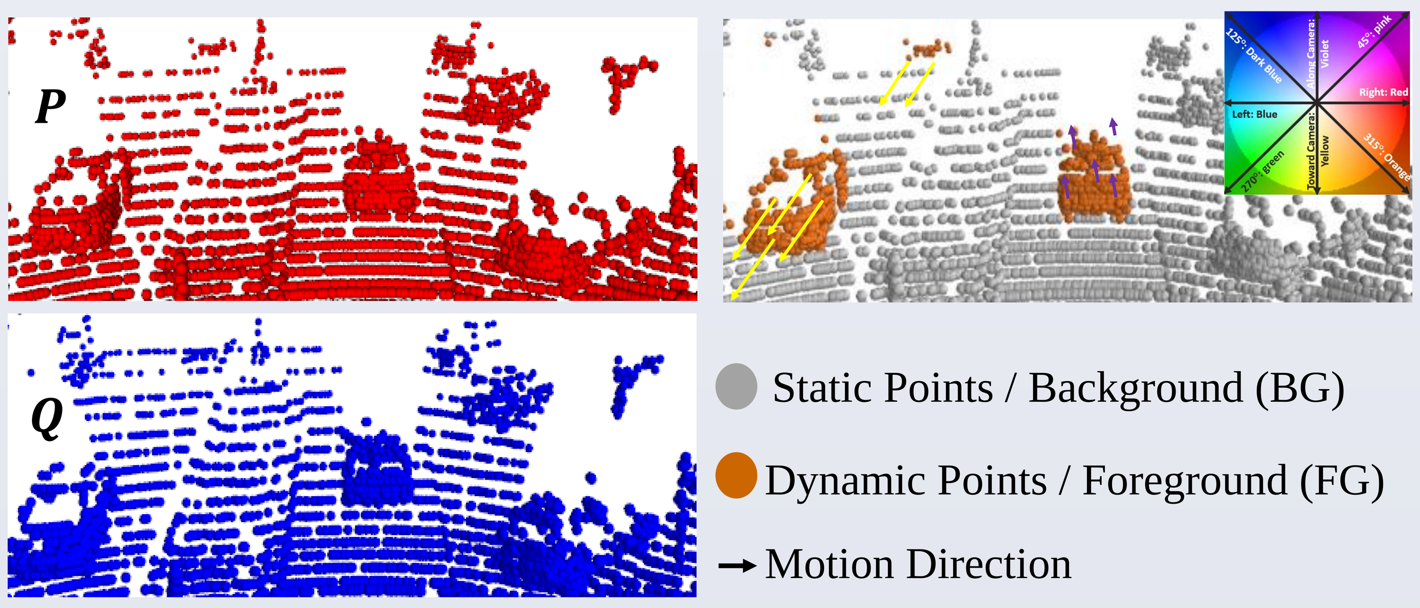
EgoFlowNet: Non-Rigid Scene Flow from Point Clouds with Ego-Motion Support

Ramy Battrawy[1], René Schuster[1], Didier Stricker[1,2]

[1]DFKI - German Research Center for Artificial Intelligence, Germany
[2]RPTU - The University of Kaiserslautern-Landau, Germany

Scene Flow Description:

- 3D Motion field estimation:
  - Represented as 3D translational vector.
- LiDAR-based / Point-based solutions:
  - Impressive results.
  - Strong generalization.
- Challenges:
  - Point-wise estimation.
  - Static points (Background) have apparent motion if the camera moves .



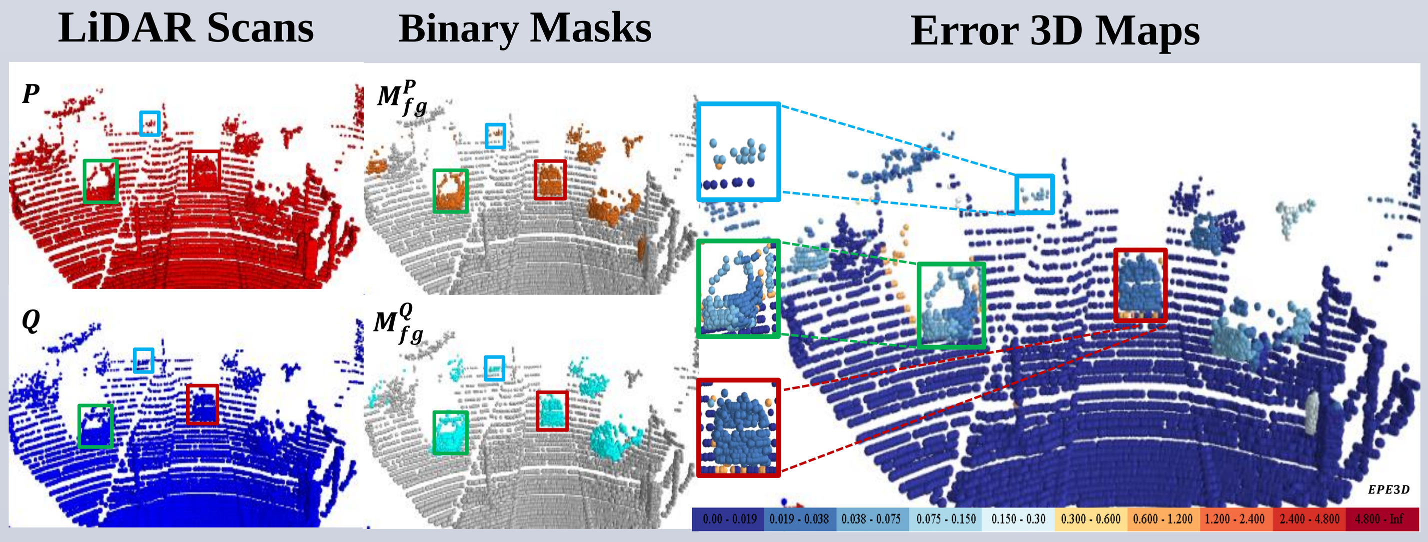
LiDAR Scans

Related Work:

- Excluding ground points.
- Superposition estimation: Dynamic objects + Ego-motion.
- Optimization based on rigidity assumption.

Our EgoFlowNet:

- Multi-task neural network architecture to jointly estimate:
  - Static / Dynamic segmentation mask.
  - Ego-motion estimation.
  - Scene flow estimation.
- Main contributions:
  - Operates non-rigidly at the point-level.
  - Free of explicit rigidity assumption (no object clustering).
  - Avoids strict iterative updates.



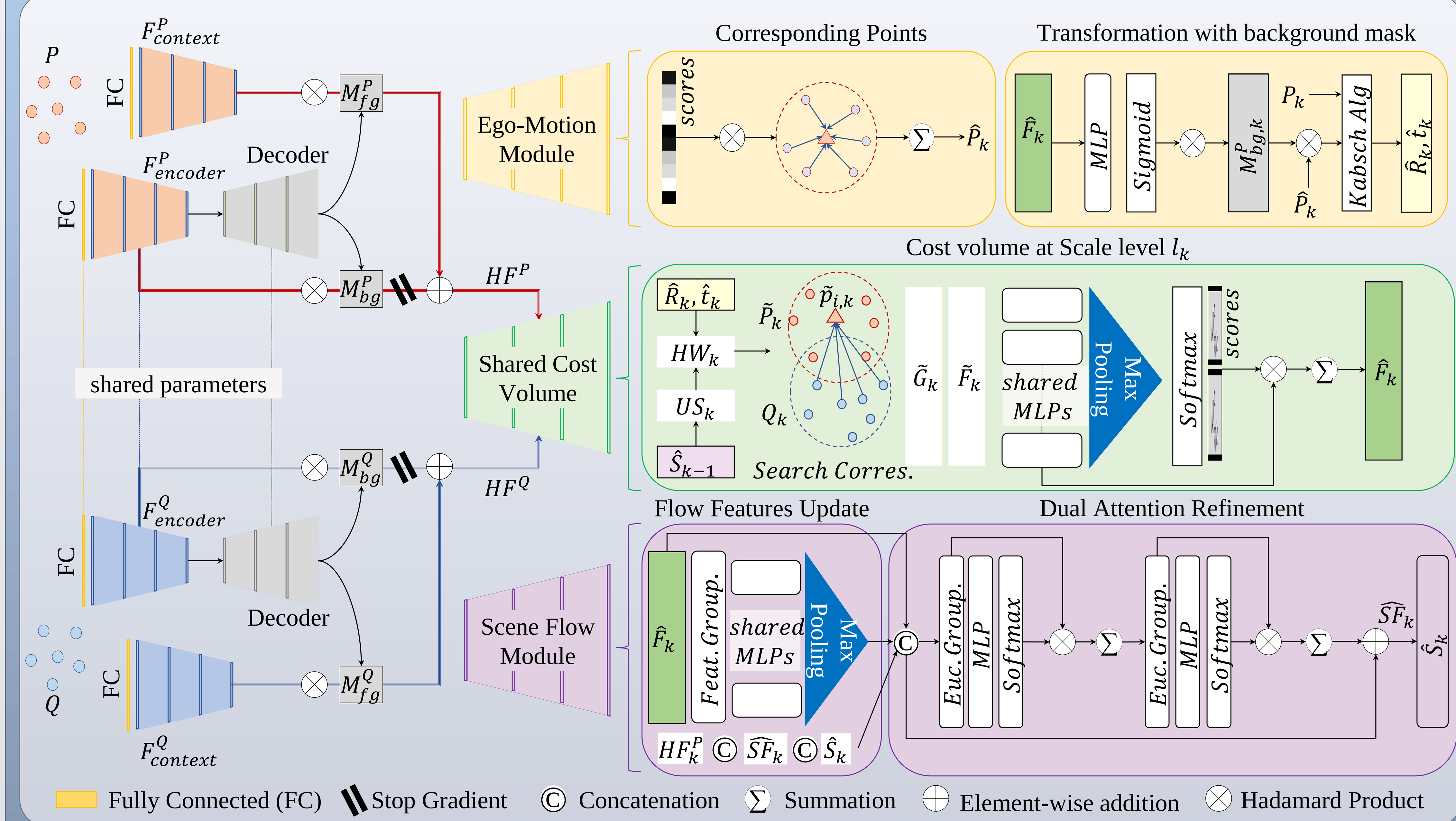
High accuracy for regions of varying local density (*e.g.*, the red, blue, and green rectangles)

EgoFlowNet Network Design:

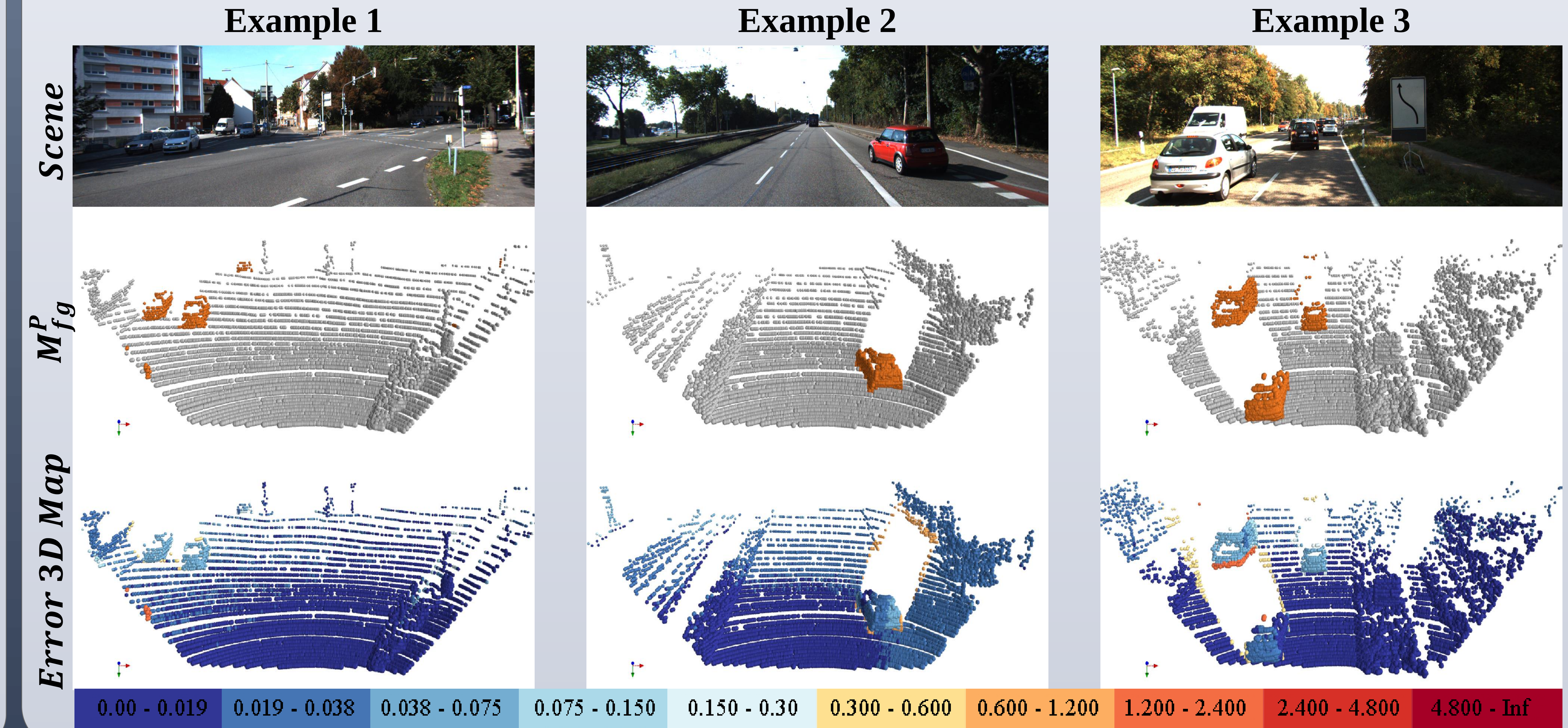
- Hierarchical point-based architecture.
  - Raw points without intermediate representation.
- Our architecture consists of:
  - Feature Extraction Module.
  - Shared Cost Volume.
  - Ego-Motion Branch.
  - Scene Flow Branch.

Our Training:

- Weakly supervised learning.
- $\mathcal{L} = \underbrace{\mathcal{L}_{seg} + \mathcal{L}_{ego}}_{\text{Fully Supervised}} + \mathcal{L}_{sf} \longrightarrow$ Self-supervised w/ Smoothness & Chamfer losses
- semanticKITTI data set [semKITTI].



Data Set	Method	Supervision	Rigidity	stereoKITTI EPE3D ↓ [m]	stereoKITTI Out3D ↓ [%]	stereoKITTI Acc3DS ↑ [%]	stereoKITTI Acc3DR ↑ [%]	lidarKITTI EPE3D ↓ [m]	lidarKITTI Out3D ↓ [%]	lidarKITTI Acc3DS ↑ [%]	lidarKITTI Acc3DR ↑ [%]
FT3Ds	PointPWC-Net	*Full*	✗	0.204	0.645	0.292	0.556	0.71	0.932	0.114	0.219
	FlowStep3D	*Full*	✗	0.109	0.391	0.577	0.765	0.797	0.929	0.087	0.184
	RMS-FlowNet	*Full*	✗	0.199	0.547	0.391	0.618	0.652	0.92	0.12	0.233
	WM3D	*Full*	✗	0.119	0.487	0.488	0.721	0.646	0.928	0.165	0.270
	Bi-PointFlowNet	*Full*	✗	0.135	0.439	0.578	0.760	0.686	0.905	0.179	0.268
	Chodosh *et al.*	*None*	✓	-	-	-	-	0.061	-	0.917	0.962
semKITTI	WSLR	*Weak*	✓	0.068	0.263	0.836	0.897	0.08	0.369	0.742	0.85
	ERC	*Weak*	✓	0.053	0.269	0.858	0.917	0.065	0.29	0.857	0.940
	Ours	***Weak***	✗	**0.039**	**0.212**	**0.922**	**0.966**	**0.049**	**0.267**	**0.918**	**0.964**



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More Details in our Paper

Contact: Ramy Battrawy
ramy.battrawy@dfki.de
http://av.dfki.de/members/battrawy