

DeepDR: Deep Structure-Aware RGB-D Inpainting for Diminished Reality

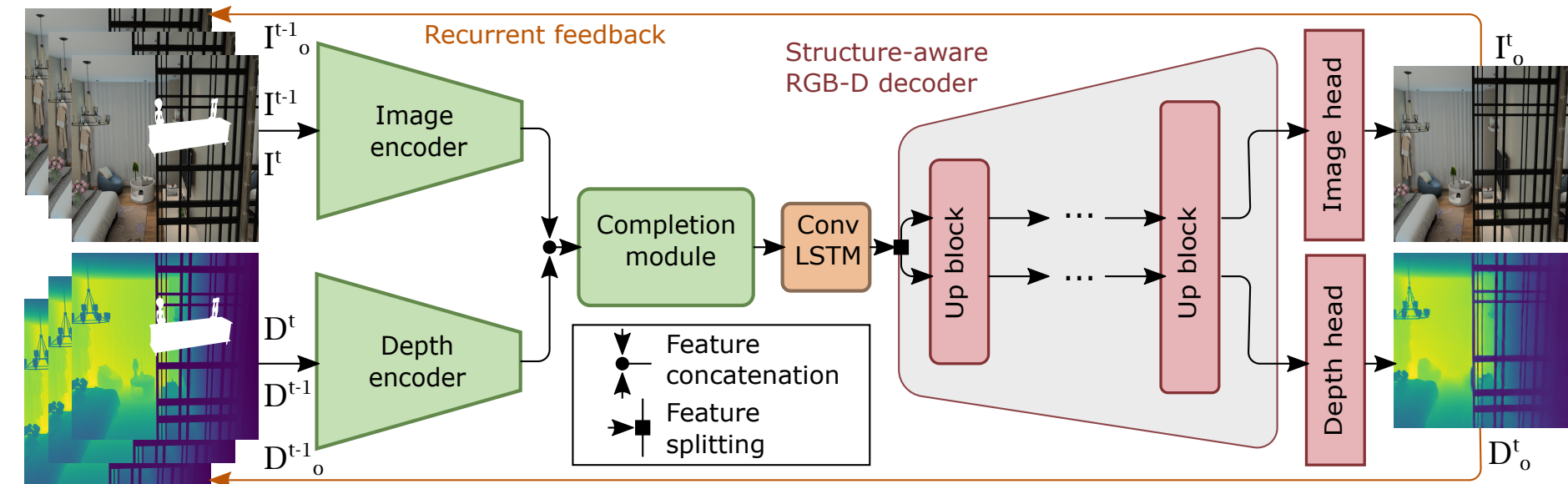
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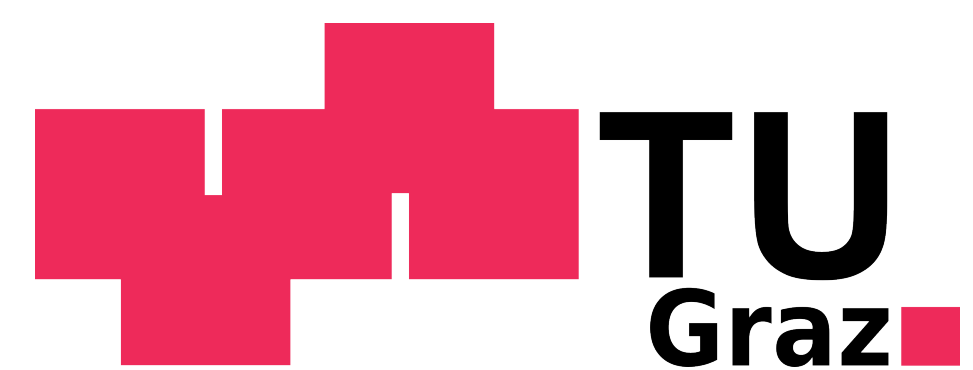
Introduction

Diminished reality (DR) involves virtually removing real objects from the environment using inpainting techniques. However, existing methods struggle with maintaining coherent structure and 3D geometry, particularly for advanced tasks like 3D scene editing. In response, we introduce DeepDR, a real-time RGB-D inpainting framework tailored for DR, ensuring both realistic image and depth inpainting with minimal artifacts, achieved through a structure-aware generative network explicitly conditioned on scene semantics.

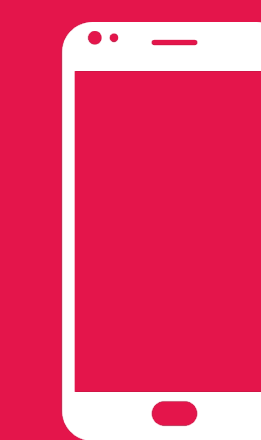
Network architecture



Input images I and depth maps D are encoded separately, then fused on a higher dimension for joint completion. Our semantics-aware decoder comprises up blocks conditioning features on semantic information. Outputs I_o^t and D_o^t serve as auxiliary inputs in a recurrent feedback loop for subsequent time steps.

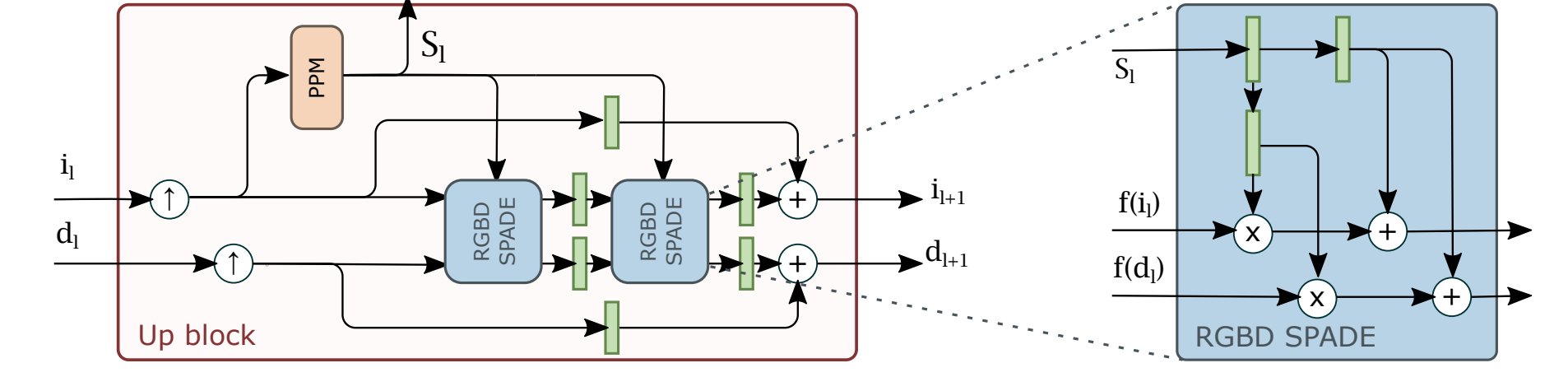


DeepDR is a framework for Diminished Reality that removes objects from the environment via real-time, structure-aware image and depth inpainting.



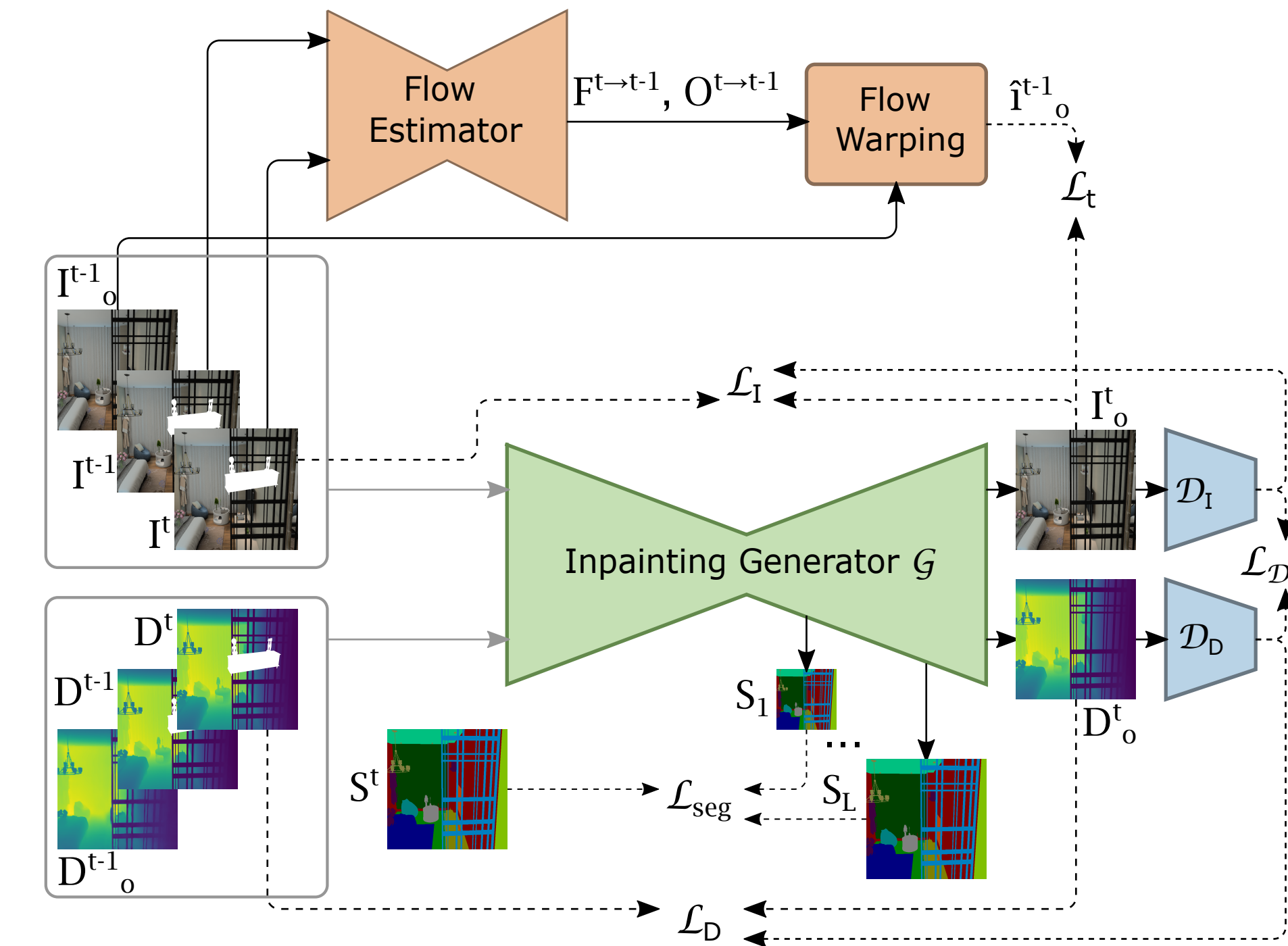
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Structure-aware RGB-D decoder



Our up blocks predict a semantic segmentation map S_i from the up-sampled image feature i_i via a pyramid pooling module. This segmentation guides the image and depth feature generation consistently.

Training



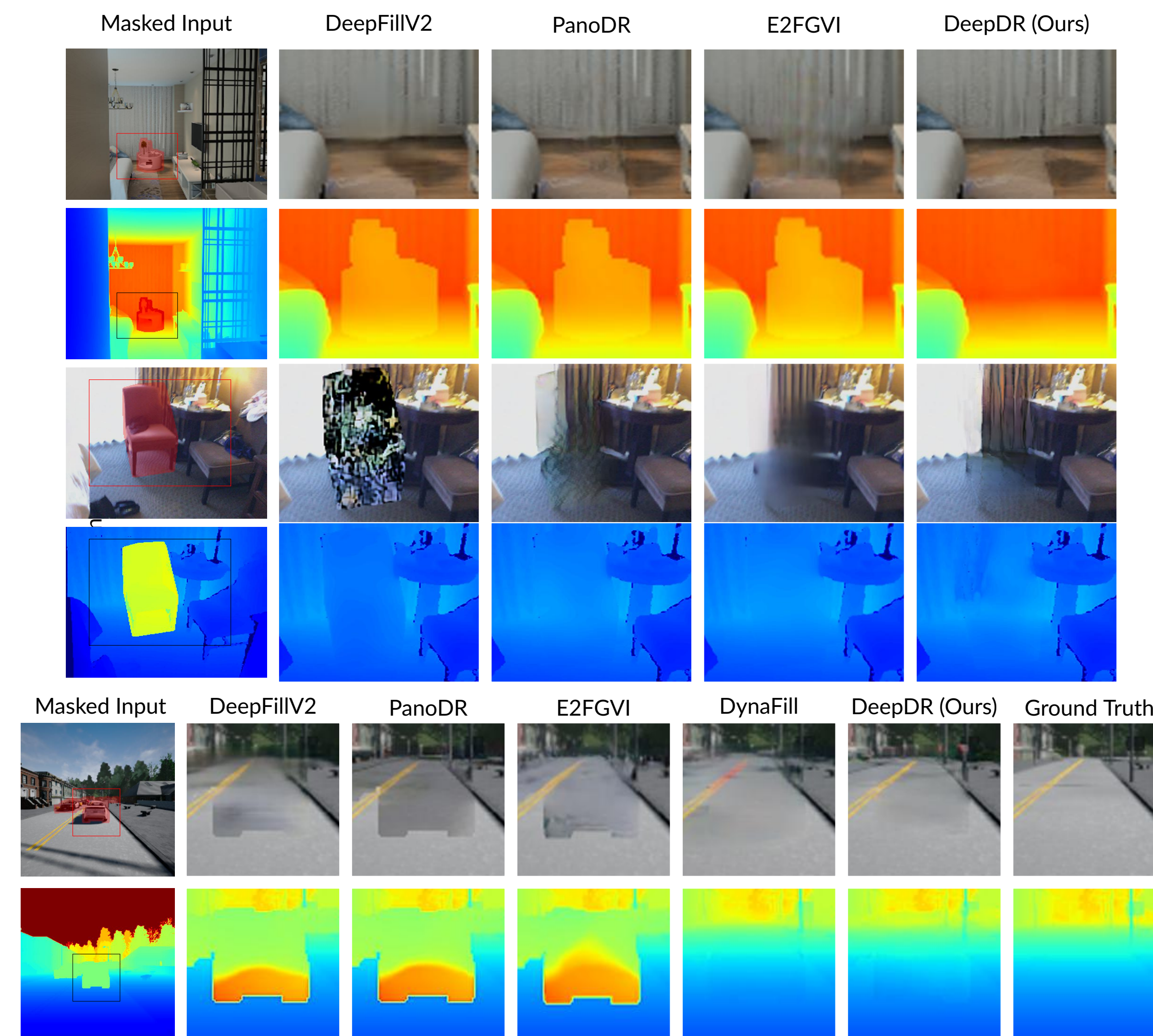
We employ loss terms and adversarial learning to enhance the accuracy and realism of inpainted RGB and depth data ($\mathcal{L}_I$, $\mathcal{L}_D$). Temporal consistency is ensured through the computation of a temporal loss $\mathcal{L}_t$ using optical flow. We enforce structural learning by incorporating semantic supervision via $\mathcal{L}_{seg}$.

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- [1] Yu et al., "Free-form image inpainting with gated convolution". In ICCV, 2019.
- [2] Giklas et al., "PanoDR: Spherical panorama diminished reality for indoor scenes". In CVPR Workshops, 2021.
- [3] Li et al., "Towards an end-to-end framework for flow-guided video inpainting". In CVPR, 2022.
- [4] Bešić et al., "Dynamic object removal and spatio-temporal RGB-D inpainting via geometry-aware adversarial learning". IEEE trans. intell. veh., 2022.
- [5] Li et al., "InteriorNet: Mega-scale Multi-sensor Photo-realistic Indoor Scenes Dataset". In BMVC, 2018.
- [6] Dai et al., "ScanNet: Richly-annotated 3d reconstructions of indoor scenes". In CVPR, 2017.

Results

We show that DeepDR can outperform related methods on three datasets qualitatively and quantitatively.



	Method	LPIPS ↓	FID ↓	Depth RMSE ↓
InteriorNet [5]	DeepFillV2 [1]	0.0150	0.448	0.572
	PanoDR [2]	<u>0.0128</u>	0.606	0.564
	E2FGVI [3]	0.0131	<u>0.363</u>	<u>0.563</u>
	DeepDR (Ours)	0.0104	0.218	0.278
DynaFill [4]	DeepFillV2 [1]	0.0238	4.122	7.92
	PanoDR [2]	0.0250	5.579	8.12
	E2FGVI [3]	<u>0.0169</u>	2.826	7.83
	DynaFill [4]	0.0197	<u>2.665</u>	<u>7.78</u>
	DeepDR (Ours)	0.0168	2.415	4.51
ScanNet [6]	DeepFillV2 [1]	0.0208	0.693	<u>0.508</u>
	PanoDR [2]	0.0119	0.348	0.536
	E2FGVI [3]	<u>0.0110</u>	<u>0.295</u>	0.512
	DeepDR (Ours)	0.0108	0.292	0.484

