Photo-realistic Neural Domain Randomization

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woven planet

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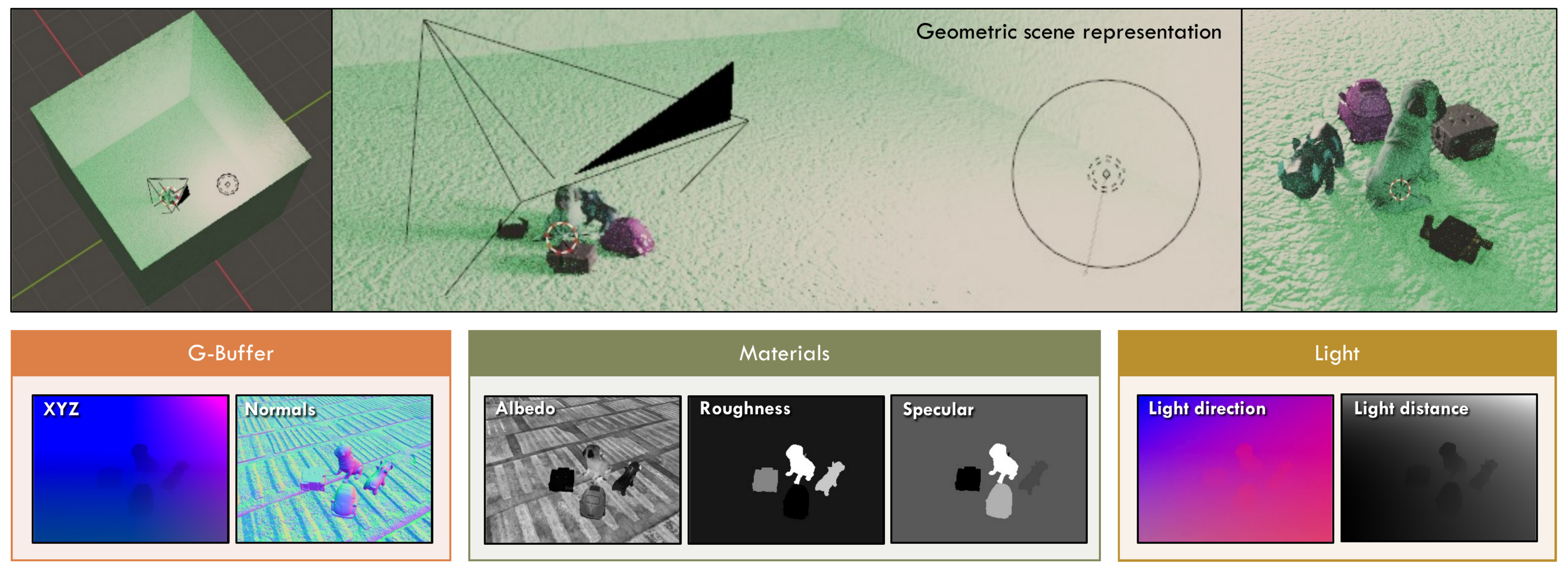
ECCV TEL AVIV 2022

Motivation

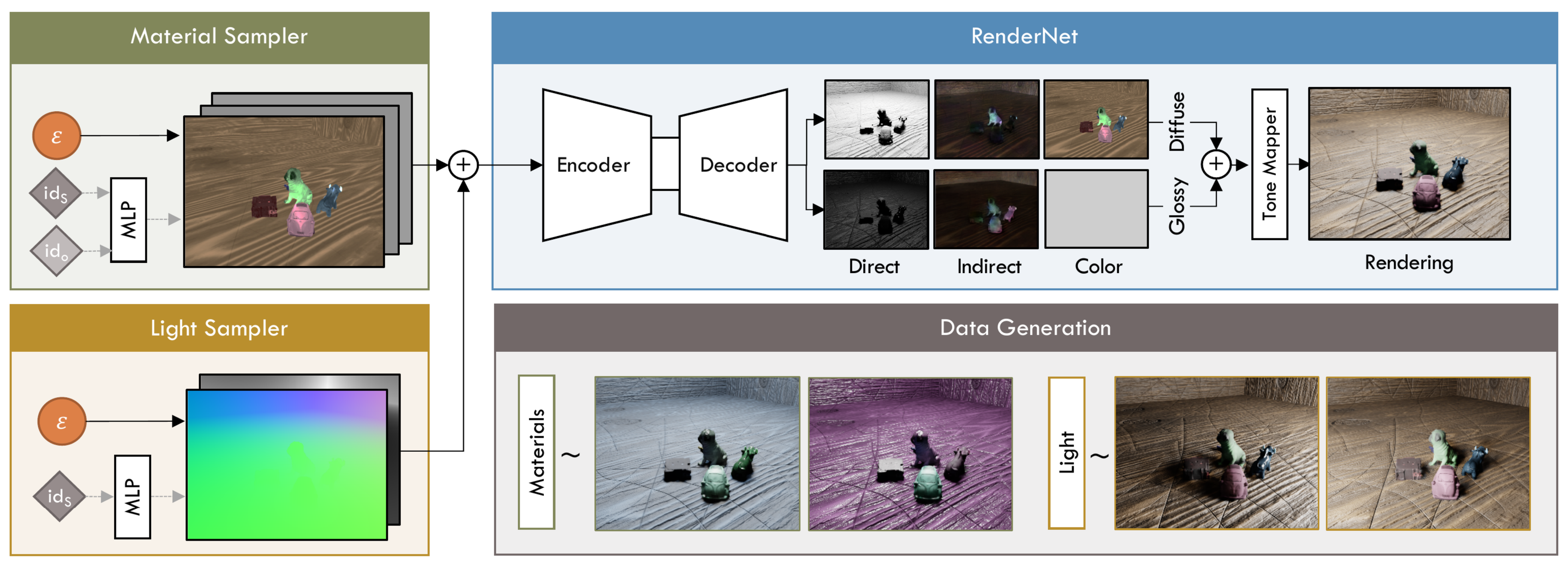
- We unify **photo-realistic rendering** and **domain randomization** for synthetic data generation
- Our learned deferred renderer, **RenderNet**, allows **flexible randomization of physical parameters** while being **1,600x** faster than comparable ray-tracers
- Our approach yields **state-of-the-art zero-shot sim-to-real transfer** for **6D object detection** and **monocular depth estimation**

Geometric Representation



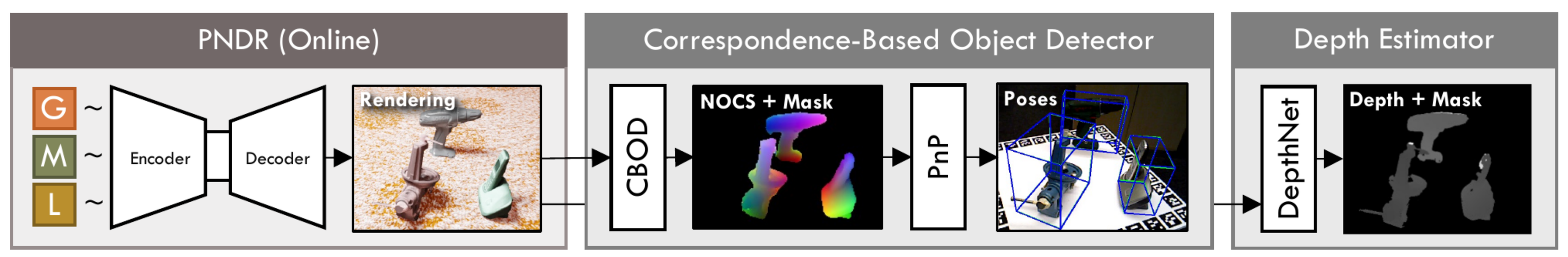
- We place 3D objects inside an empty room ensuring no collisions. **Random materials** are assigned to objects and walls and a **randomly positioned light source** illuminates the scene.
- Output buffers consist of **G-Buffer** (scene coordinates in camera space *X*, surface normals map *N*), **material properties** (albedo *A*, roughness *R*, specularity *S*), and **lighting** (light direction map L_{dir}, and light distance map L_{dist})

Method



- The main component of our domain randomization method is the ray tracer approximator (**RenderNet**). It takes a **G-buffer** as well as random **material maps** and **light maps** produced by corresponding samplers and generates intermediate light outputs. These outputs are then combined using a **tone mapper** to generate a final rendering.
- The lower-right row shows different material and light samples (e.g., roughness, specularity, light position).

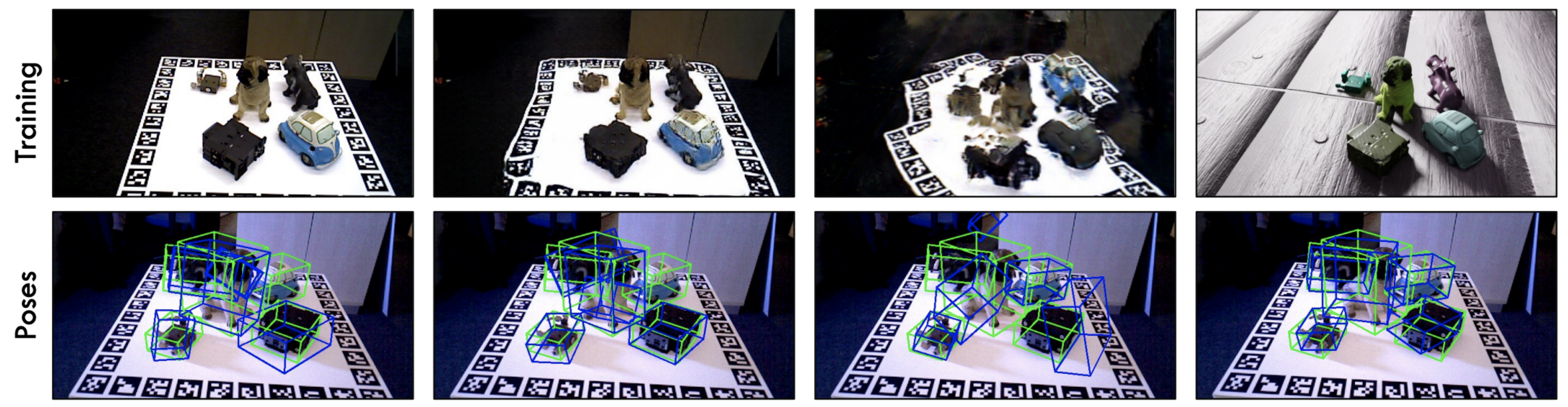
Downstream Tasks



- During training, downstream tasks take PNDR renderings generated **online**, providing new realistic augmentations **at each iteration**.

Results

Dynamic Lighting Benchmark: Training on photorealistic synthetic data is competitive with real data training and generalizes better to new domains.



(a) Real (b) Pix2PixHD (c) CUT (d) PNDR

Train	Method	HB Scene 5						HB Scene 10 (Lighting)					
		Car	P12	P15	Pumba	Dog	Mean	Car	P12	P15	Pumba	Dog	Mean
Real		91.76	94.12	79.34	94.41	95.00	90.93	26.69	35.88	8.75	25.22	14.63	22.24
Real + CAD†	Pix2Pix [22]	81.84	76.47	38.53	76.76	94.12	73.54	37.13	35.59	13.75	24.78	33.82	29.01
	Pix2PixHD [56]	90.96	92.21	73.09	91.91	95.00	89.59	37.21	40.96	21.25	29.26	15.59	32.33
Real + CAD‡	CycleGAN [66]	49.41	31.10	24.12	40.88	73.24	43.75	27.72	2.28	6.91	7.06	11.47	11.09
	CUT [40]	56.10	28.97	29.34	41.47	85.29	66.49	27.35	4.63	7.35	8.90	12.13	25.36
CAD	RayTraced - 1088	85.59	86.76	61.18	89.71	94.85	83.62	47.28	36.84	9.12	36.25	23.38	30.57
	RayTraced - 2176	86.99	90.00	63.01	91.47	95.00	85.29	50.88	38.82	10.00	35.29	30.96	33.19
	RayTraced - 4352	89.71	88.97	66.91	92.35	95.00	86.59	52.43	38.75	10.29	41.47	43.82	37.35
	Ours - 1088	89.93	91.62	71.99	92.35	95.00	88.18	58.01	42.50	10.59	46.18	44.93	40.44

6D Object Detection

Method	Training	HB5			HB10		
		AbsRel↓	RMSE↓	a1↑	AbsRel↓	RMSE↓	a1↑
Monodepth2	Raytraced	0.082	0.09	0.951	0.162	0.148	0.805
	PNDR	**0.075**	**0.083**	**0.966**	**0.154**	**0.14**	**0.83**
PackNet-SfM	Raytraced	0.11	0.111	0.884	0.141	0.136	0.833
	PNDR	**0.082**	**0.087**	**0.977**	**0.135**	**0.131**	**0.852**

Monocular Depth Estimation

Generalization & Ablation

Train	Test	PSNR↑	SSIM↑	LPIPS↓
HB_2 - Train	HB_2 - Train	30.36	0.96	0.03
	HB_2 - Test	26.14	0.94	0.05
	HB_5 - Test	24.14	0.92	0.06
HB_5 - Train	HB_5 - Train	30.39	0.96	0.03
	HB_5 - Test	26.40	0.94	0.06
	HB_2 - Test	23.72	0.92	0.07

We achieve strong **generalization** performance when PNDR is applied on a completely different scene containing **new objects** and **materials**.

	Modes	ADD_{AUC} ↑	IoU ↑	Corr (mm) ↓
Material	A	85.43	83.29	38.56
	$+S+R$	3%	3%	11%
Light	Fixed	73.04	72.24	76.94
	Dynamic	21%	19%	55%
Rendering	D_{dir}, G_{dir}	87.09	85.55	38.42
	$+ D_{ind}, G_{ind}$	1%	0%	11%
Full		88.18	85.97	34.32

We analyze the effect of different augmentations on downstream task performance. Lighting is by far the most important randomization parameter.