

Learning 3D-aware Image Synthesis with Unknown Pose Distribution

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Motivation: Quality is affected by pose distribution

Good pose distribution



CAMPARI



Good initialization



Bad pose distribution



Bad initialization

 Image: Sector of the sector

 Inaccurate pose priors lead to faulty shapes.
Hard to get accurate annotations for all types of data.

Free the model from the requirements of pose priors! PoF3D

Pose-free Generator

Learn poses from latent space

$$G(z,\xi) = I \sim p_{\theta}(I|z,\xi) \quad \longrightarrow \quad G(z,\Psi(z)) = I \sim p_{\theta}(I|z,\Psi(z))$$



Pose-aware Discriminator

■ To facilitate generator synthesizing correct geometry

- Learn pose prediction from the generator
- The inferred pose is treated as a pseudo label for conditional real/fake classification





• Overview



Qualitative Comparison















EG3D (with ground-truth poses)

Ours (without pose priors)

Evaluation Metrics

- Depth error
- Pose error
- Jensen–Shannon Divergence (JS)



Quantitative Results

		FFI	ShapeNet Cars			
	FID	Depth	Pose	JS	FID	JS
CAMPARI	58.59	1.78	0.15	0.61	68.91	0.72
CAMPARI+EG3D	3.25	1.13	0.20	0.73	4.66	0.83
EG3D	4.80	0.29	0.08	-	9.68	-
Ours	4.99	0.29	0.11	0.20	3.78	0.51

Ablation Study

	FFHQ							
	FID	Depth	Pose	RE	JS			
w/o symmetry loss	4.50	0.41	0.12	0.030	0.20			
w/o pose-aware D	3.43	1.30	0.20	0.046	0.21			
lr = 2.5e-4	122.07	0.82	0.74	0.051	0.56			
lr = 2.5e-6	10.20	0.70	0.16	0.173	0.38			
Ours	4.99	0.29	0.11	0.037	0.20			

Pose Distribution

• Generator



Pose Distribution

• Discriminator



Take-home Message

- Pose is crucial for 3D-aware image synthesis. Bad pose priors can hurt the synthesis quality.
- Derving poses from the latent space and making the discriminator pose-aware can enable 3D-aware image synthesis without pose priors.







Github

Paper

Project Page

Demo