NeRF-GAN Distillation for Efficient 3D-Aware Generation with Convolutions



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80 Batch Size

ins²	Martin Danelljan ¹	Danda Paudel ¹	Luc Van Gool ¹	
ırich	³ ML & Robotics,	CSEM, Switzerland		
		Method		
The	e Proposed Meth	od		
Moo Train	 A convolutional get the pretrained NeR ning The pretrained NeF Reconstruction and 	nerator conditioned F-GAN and the targe RF-GAN as the teach adversarial objectiv	I on the latent code of et viewpoint er for supervision ves	
Z	Mapping Network	Volumetric Renderer L ^L Rec	Super Resolution	
Froze	en weights Trained	Resolution	Discr. Ladv	
	• Stage 1 training or	nly with reconstructi	ion loss	
	 Stage 1: training of Stage 2: training wi 	ith reconstruction a	nd adversarial losses	
Th	ne proposed two-stage	e training leads to be	etter 3D consistency!	
Mit	tigating Pose-Att	ribute Correlat	ion	
	 Convolutional generic in the training data Mitigate the bias be data as real sample 	erators are prone to a by mixing real and N es for the adversaria	eRF-GAN-generated al training	
Githuk https:/): //github.com/mshahba	azi72/NeRF-GAN-Di	stillation	
Email:				

mshahbazi@vision.ee.ethz.ch



Quantitative Comparison of Visual Quality

Method	FFHQ		AFHQ		ShapeNET Cars	
	$FID\downarrow$	$KID\downarrow$	$FID\downarrow$	$KID\downarrow$	$FID\downarrow$	$KID\downarrow$
EG3D [5]	5.0	0.0018	2.9	0.0003	3.5	0.0017
PC-GAN	19.3	0.0085	4.5	0.0009	6.1	0.0018
LiftGAN [48]	29.8*	-	-	-	-	-
SURF	31.1	0.0153	-	-	-	-
Ours (ST2)	6.6	0.0019	3.8	0.0011	3.1	0.0013
Ours (ST3)	6.8	0.0023	3.2	0.0007	3.1	0.0012

Quantitative Comparison of 3D Consistency

Method	Pose Acc. \downarrow	3D Landmark \downarrow	ID ↑
EG3D [5]	0.002	0.018	0.75
PC-GAN	0.009	0.062	0.56
SURF	0.044	0.014	0.86
Ours (ST2)	0.002	0.023	0.75
Ours (ST3)	0.002	0.022	0.75

Examples of Inversion and Editing using Our Method

