DeepVoxels: Learning Persistent 3D Feature Embeddings — Supplemental Document —

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1. DeepVoxels Submodule Architectures Feature extraction network Rendering Network 3D Inpainting Network All layers with 0.2 dropout prob. From Projection From Integration Image conv3x3/1 512x512x3 64x64x64 conv3x3/1 32x32x32x64 conv4x4x4/2 512x512x64 conv4x4/2 64x64x256 conv4x4/2 16x16x16x64 conv4x4x4/2 256x256x64 conv3x3/1 32x32x512 conv3x3/1 8x8x8x128 conv4x4x4/2 256x256x64 conv4x4/2 32x32x512 conv4x4/2 conv4x4x4/2 4x4x4x256 128x128x128 conv3x3/1 16x16x512 conv3x3/1 2x2x2x256 dconv4x4x4/2 128x128x128 conv4x4/2 16x16x512 conv4x4/2 4x4x4x(256+256) dconv4x4x4/2 8x8x512 conv3x3/1 64x64x256 conv3x3/1 8x8x8x(128+128) dconv4x4x4/2 64x64x256 conv4x4/2 8x8x512 conv4x4/2 16x16x16x(64+64)dconv4x4x4/2 conv3x3/1 4x4x512 32x32x512 conv3x3/1 32x32x512 conv4x4/2 4x4x512 conv4x4/2 32x32x32x(64+64) conv4x4x4/2 32x32x32x64 To projection 16x16x512 conv3x3/1 2x2x512 dconv4x4/2 4x4x512 conv3x3/1 16x16x512 conv4x4/2 8x8x512 conv3x3/1 dconv4x4/2 4x4x(512+512) Occlusion Network 8x8x512 8x8x512 conv3x3/1 conv4x4/2 From projection 32x32x56x64 conv3x3x3/1 dconv4x4/2 4x4x512 conv3x3/1 8x8x(512+512) 16x16x512 conv3x3/1 4x4x512 conv4x4/2 32x32x56x4 conv4x4x4/2 dconv4x4/2 16x16x(512+512 dconv4x4/2 16x16x28x4 conv4x4x4/2 conv3x3/1 32x32x512 4x4x512 conv3x3/1 8x8x14x8 conv4x4x4/2 4x4x(512+512) dconv4x4/2 32x32x (512+51) dconv4x4/2 4x4x7x16 dconv4x4x4/2 8x8x512 conv3x3/1 64x64x256 conv3x3/1 8x8x14x(8+8) dconv4x4x4/2 8x8x(512+512) dconv4x4/2 64x64x(256+64 dconv4x4/2 16x16x28x(4+4 16x16x512 conv3x3/1 128x128x256 dconv4x4x4/2 conv3x3/1 32x32x56x(4+4 conv3x3x3/1 16x16x(512+512 dconv4x4/2 128x128x256 dconv4x4/2 32x32x512 conv3x3/1 256x256x64 conv3x3/1 Depthwis Softmax 32x32x (512+512 dconv4x4/2 To depthwise dconv4x4/2 32x32x56x1 weighted sum 64x64x256 conv3x3/1 512x512x64 conv3x3/1 conv3x3/1 64x64x(256+256) 512x512x64 conv3x3/1 64x64x64 To lifting 512x512x32 conv3x3/1 512x512x3 TanH + BatchNorm + LeakyReLU • + BatchNorm + ReLU Novel View

Figure 1: Precise architectures of the feature extraction, rendering, inpainting and occlusion networks. They all follow the basic U-Net structure, while following general best practices in generative network architectures: Reflection padding instead of zero padding, kernel size divisible by stride.



2. Baseline Architecture Tatarchenko et al. [2]

Figure 2: Architectural details of the autoencoder baseline model with latent pose concatenation as proposed by Tatarchenko et al. [2].

3. Baseline Architecture Worrall et al. [3]

Enco	oder	D
		AII Idyers wit.
Image	I	From featur transform
512x512x3	conv3x3/1	3x1850
512x512x64	conv4x4/2	
256x256x64	conv3x3/1	4x4x512
256x256x64	conv4x4/2	4x4x512
128x128x128	conv3x3/1	2x2x512
128x128x128	conv4x4/2	4x4x512
64×64×256	copy3x3/1	4x4x512
64x64x256	conv4x4/2	8x8x512
		8x8x512
32x32x512	conv3x3/1	16x16x512
32x32x512	conv4x4/2	16x16x512
16x16x512	conv3x3/1	32x32x512
16x16x512	conv4x4/2	32×32×512
8x8x512	conv3x3/1	64x64x256
8x8x512	conv4x4/2	
4x4x512	conv3x3/1	64x64x256
4x4x512	conv4x4/2	128x128x256
2x2x512	dconv4x4/2	128×128×256
4x4x512	conv3x3/1	256x256x128
4 4 510	f= 2+1050	256x256x128
4x4x512	10 3x1850	512x512x64
3x1850	To feature transform	512x512x64
	1	512x512x32
	1	512x512x3

Dec l layers with	oder 0.2 dropout prob.
From feature transform	
3x1850	fc 4x4x512
4x4x512	conv3x3/1
4x4x512	conv4x4/2
2x2x512	dconv4x4/2
4x4x512	conv3x3/1
4x4x512	dconv4x4/2
8x8x512	conv3x3/1
8x8x512	dconv4x4/2
16x16x512	conv3x3/1
16x16x512	dconv4x4/2
32x32x512	conv3x3/1
32x32x512	dconv4x4/2
64x64x256	conv3x3/1
64x64x256	dconv4x4/2
128x128x256	conv3x3/1
128x128x256	dconv4x4/2
256x256x128	conv3x3/1
256x256x128	dconv4x4/2
512x512x64	conv3x3/1
512x512x64	conv3x3/1
512x512x32	conv3x3/1
512x512x3	TanH
Novel View	1

Fully	Connected	+	LeakyReLU
• +	BatchNorm	+	LeakyReLU
• +	BatchNorm	+	ReLU

Figure 3: Architectural details of the baseline model based on a rotation-equivariant latent space as proposed by Worrall et al. [3].

4. Baseline Architecture Pix2Pix (Isola et al. [1])



Figure 4: Architectural details of the image-to-image translation baseline model based on Pix2Pix by Isola et al. [1].

5. Comparison of ground-truth depth to estimated depth



Figure 5: Comparison of ground truth depth maps and the depth maps implicit in the DeepVoxels voxel visibility scores (upsampled from a resolution of 64×64 pixel). We note that these depth maps are learned in a fully unsupervised manner (at no time does our model see a depth map), and only arise out of the necessity to reason about voxel visibility. The background of the depth map is unconstrained in our model, which is why depth values may deviate from ground truth.

6. Pose Extrapolation



Figure 6: Our training set comprises views sampled at random on the surface of the northern hemisphere. Images in each row are consistently scaled and cropped. We show views that require the model to extrapolate more aggressively - such as increasing the camera distance by a factor of 1.3 (top row), decreasing the camera distance by a factor of 0.75 (middle row) or leaving the northern hemisphere altogether and sampling from the southern hemisphere (bottom row). We show a comparison of ground truth (left column), our model output (center column), and the nearest neighbor in the training set (right column). For the proposed model, detail is lost especially in cases where the model has either never seen these points on the object (bottom row), or where details are seen from closeby for the first time (middle row). Generally, however, the performance degrades gracefully - rigid body motion and general geometry stay consistent, with loss in fine-scale detail and a few failures in occlusion reasoning.

7. Real-World Results

Here, we outline additional details on data captured with a digital single-lens reflex camera as shown in the supplementary video. For this experiment, we captured 457 photographs of a statue. The resolution of each photograph was 1920×1080 pixels. We use sparse bundle adjustment to estimate intrinsic and extrinsic camera parameters. Photographs were subsequently symmetrically center-cropped and downsampled to a resolution of 512×512 pixels. Zoom and focus were set at fixed values throughout the capture. The rest of the processing pipeline is identical to the computer-generated data discussed in the main paper.

References

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