Supplementary for Continuous Levels of Detail for Light Field Networks

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1 Additional Details

The pseudocode for our training algorithm is shown in Algorithm 2. For our experiments, we use a neural network with 10 layers and continuous levels of detail from 1.0 up to 385.0. The parameters for our network are laid out in Table 1.

Algorithm 1: Training Procedure Pseudocode for Continuous LOD LFNs

```
Data: Training images with poses
Result: Trained LFN with continuous LODs
lfn ← InitializeLFN()
optimizer ←Adam(lfn)
for epoch 1 to num_epochs do
    for images ← GetImageBatch() do
        sat ← ComputeSAT(images)
        ray_pdf ← ComputeRayPDF(images)
        for rays, colors ← SampleRays(ray_pdf) do
            low_lod, low_lod_scale ← SampleLOD()
            low_lod_colors ← SampleSAT(sat, rays, low_lod_scale)
            loss ← L2(lfn(rays, max_lod), colors) +
              L2(lfn(rays, low_lod), low_lod_colors)
            loss.backward()
            optimizer.step()
        end
    end
end
```

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Algorithm 2: Neuron Masking Pseudocode for Continuous LOD LFNs

Data: Input feature f from the variable-width linear layer and fractional LOD α
Result: Masked feature f'
$f' \leftarrow \text{cat}(f[:,:-1], \alpha * f[:,-1:], \text{dim=-1})$

Table 1: Model Parameters for Each Level of Detail.

Level of Detail	1.0	ℓ	385.0
Model Layers	10	10	10
Layer Width	128	$127 + \lceil \ell \rceil$	512
Parameters	135,812	$\approx 9 * (127 + \ell)^2$	2,116,100
Model Size (MB)	0.518	$\approx 36 * (127 + \ell)^2 / 2^{20}$	8.072
Target Scale	1/8	$2^{\wedge}\left(4(\frac{127+\ell}{512}) - 4\right)$	1

2 Additional Results

We present some qualitative results in Figure 1. Additional qualitative results are available on our supplementary webpage.

2.1 Comparision to NeRF

Neural radiance fields use volume rendering and 3D scene coordinates which provide 3D scene structure and multi-view consistency at the cost of requiring dozens to hundreds of evaluations per ray. Two continuous LOD methods for NeRFs are Mip-NeRF [1] and Zip-NeRF [2]. Mip-NeRF uses integrated positional encoding to approximate a canonical frustum around a ray while Zip-NeRF uses multisampling of feature grid. Both of these methods are targeted solely toward anti-aliasing and flicker reduction rather than towards resource adaptivity. Hence, the entire model must be downloaded for rendering and the performance per pixel is the same at each scale. Furthermore, neither method is directly applicable to light field networks which rely on the spectral bias of ReLU MLPs and thus are incompatible with positional encoding and feature grids.

For reference purposes, we present quantitative results using Mip-NeRF [1] to display our datasets in Table 2. We train Mip-NeRF for 1 million iterations with a batch size of 1024 rays with the same 67% foreground and 33% background split in each batch. We also use the same training and test split for each dataset as in our experiments.

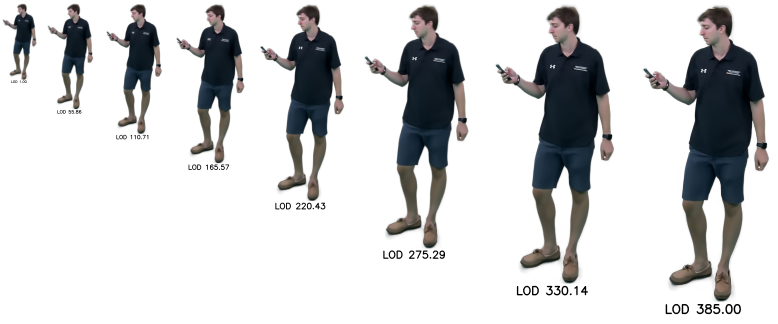
Table 2: Average Rendering Quality Comparison

Model	1/8	1/4	1/2	1/1
Continuous LOD LFN	28.06	29.79	28.44	27.40
Mip-NeRF	24.81	24.95	24.35	23.86

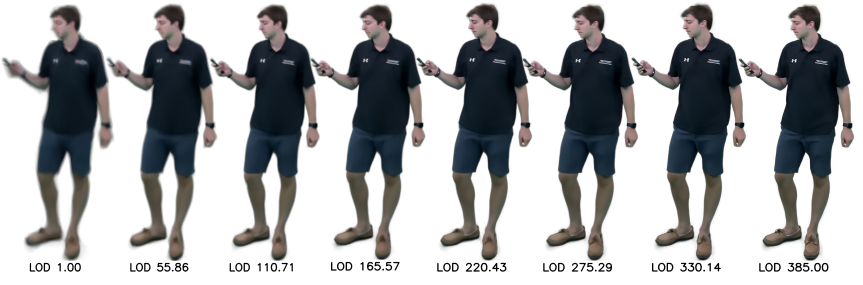
(a) PSNR (dB) at 1/8, 1/4, 1/2, and 1/1 scale.

Model	1/8	1/4	1/2	1/1
Continuous LOD LFN	0.8380	0.8751	0.8487	0.8455
Mip-NeRF	0.6819	0.6735	0.6451	0.6374

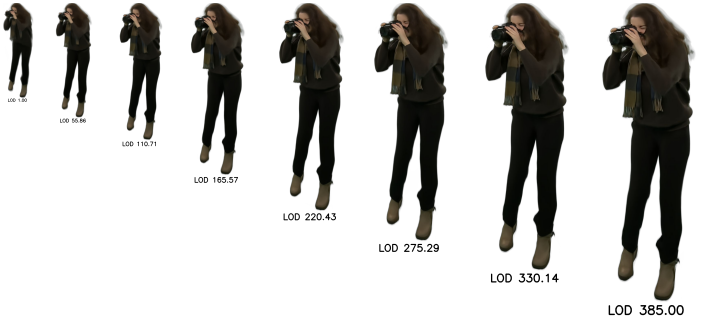
(b) SSIM at 1/8, 1/4, 1/2, and 1/1 scale.



(a) Dataset A LODs shown at various scales



(b) Dataset A LODs shown at the same scale



(c) Dataset C LODs shown at various scales

(d) Dataset C LODs shown at the same scale

Figure 1: Qualitative results rendering our continuous LFNs at multiple levels of detail for two datasets.

Figure 2: Mip-NeRF rendering.

In our experiments, we observe that with our sampling scheme, Mip-NeRF is not able to separate the foreground and background cleanly as shown in Figure 2 which leads to worse PSNR and SSIM results.

In general, NeRF-based methods are better able to perform view-synthesis with high-frequency details due to their use of positional encoding and their 3D structure. MLP-based methods such as Mip-NeRF typically have a compact size ($\leq$ 10 MB) but suffer from slow rendering times on the order of tens of seconds per image. Feature-grid NeRFs such as Instant-NGP [4], Plenoxels [5], and Zip-NeRF [2] can achieve real-time rendering but at the cost of larger model sizes ($\geq$ 30 MB). Factorized feature grids such as TensorRF [3] promise both fast rendering and small model sizes. Note that the goal of our paper is to enable more granularity with continuous levels of detail for rendering and streaming purposes rather than improving view-synthesis quality.

References

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[4] Thomas Müller, Alex Evans, Christoph Schied, and Alexander Keller. Instant neural graphics primitives with a multiresolution hash encoding. *ACM Trans. Graph.*, 41(4), jul 2022. ISSN 0730-0301. doi: 10.1145/3528223.3530127. URL https://doi.org/10.1145/3528223.3530127.

[5] Alex Yu, Sara Fridovich-Keil, Matthew Tancik, Qinhong Chen, Benjamin Recht, and Angjoo Kanazawa. Plenoxels: Radiance fields without neural networks, 2021.