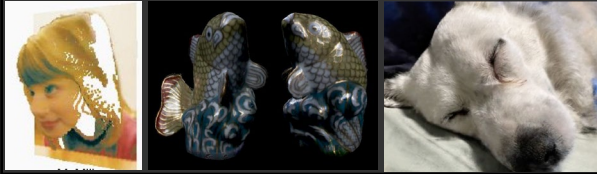


## Image-Based Rendering

CSE 274, Lecture 10: Beyond NeRFs

Ravi Ramamoorthi

<http://www.cs.ucsd.edu/~ravir>



1

## To Do

2

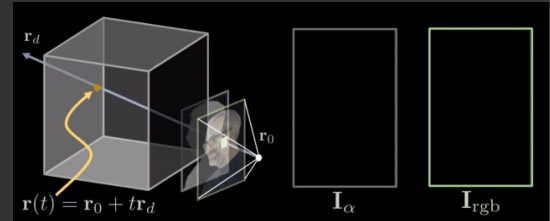
## Motivation

- Neural Radiance Fields key for view synthesis
- Tons of follow-on work, best papers at almost every subsequent vision/graphics/learning conference
- We talk at a high level about a few key developments
  - Antialiasing (MIPNerf etc.)
  - Feature Grids: Triplanes (EG3D), TensoRF
  - InstantNGP
  - Gaussian Splatting
  - Single Image methods and GenAI
  - Stochastic Geometry Fields
- Only small subset, thousands of papers each year

3

## Neural Volumes

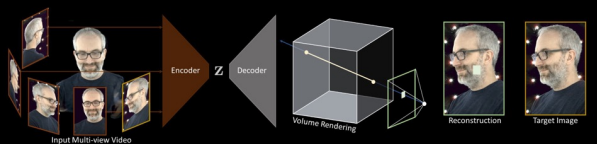
- Neural volumes, differentiable ray marching
- Volume explicit voxel grid, using CNN
  - Considered MLPs like NeRF but w/o positional encoding



Lombardi et al. SIGGRAPH 2019  
Seminal paper volume rendering, points to NeRFs, doesn't get due recognition always

4

## Neural Volumes



- Many Key Ideas
  - Volumetric not surface representation (as regular grid)
  - Neural network representation of volume
  - Directly optimize loss with respect to reconstruction
  - Differentiable Ray Marching
- Subsequent work retains notions above (note: gaussian splatting does not use a neural network)

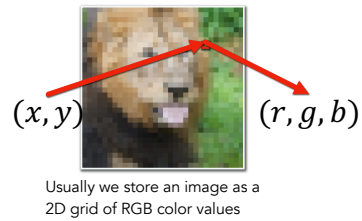
5

## Neural Radiance Fields (NeRF)

Mildenhall, Srinivasan, Tancik, Barron, Ramamoorthi, Ng 20

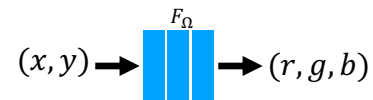
6

Toy problem: storing 2D image data



7

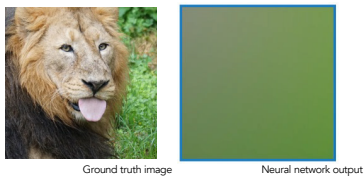
Toy problem: storing 2D image data



What if we train a simple fully-connected network (MLP) to do this instead?

8

Naive approach fails!



9

**Problem:**

“Standard” coordinate-based MLPs cannot represent high frequency functions

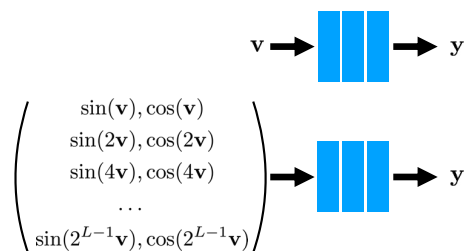
10

**Solution:**

Pass input coordinates through a high frequency mapping first

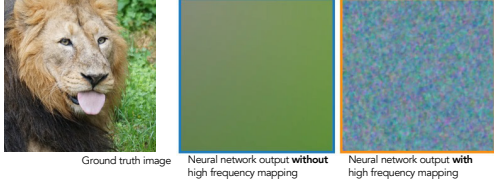
11

Example mapping: “positional encoding”



12

Problem solved... but why?



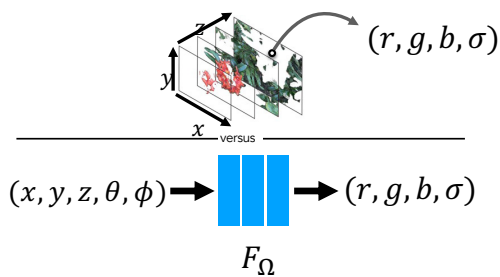
13

## Fourier Features Let Networks Learn High Frequency Functions in Low Dimensional Domains

Tancik et al., NeurIPS 2020

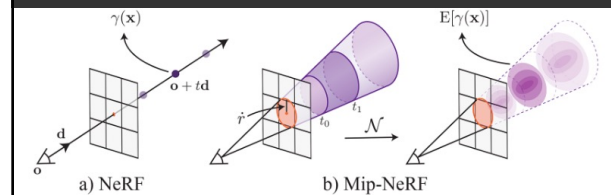
14

Use neural network to replace large N-d array



15

## Mip-NeRF



- <https://www.youtube.com/watch?v=EpH175PY1A0&t=11s>
- Subsequent work: MipNeRF360 (CVPR 22); Tri-MipNeRF, ZipNeRF (ICCV 23); Rip-NeRF (SIG 24)

Barron et al. ICCV 2021

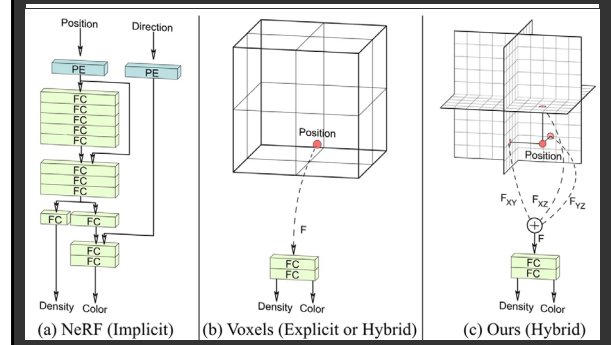
16

## Feature Fields

- Neural Volumes and NeRFs are two extremes
  - Purely explicit voxel grid vs compact neural (large) MLP
- Hybrid representations: Feature Grids
  - Coarse voxel grid of abstract features
  - Smaller (often just 2-layer) MLP to decode features to standard volume density and color as in NeRF
  - No positional encoding needed any more, only features
- Memory-Time tradeoff: more memory for faster computation time and training
- Explosion in types of feature grids (and some revisiting PRT and early light transport)
- Gaussian splatting uses gaussians, no MLP at all

17

## TriPlanes EG3D



Chan et al. CVPR 22. <https://nvlabs.github.io/eg3d/>

18

[illegible]

21

The figure consists of three main components arranged horizontally. On the left is a photograph of a physical LEGO Technic bulldozer model built on a wooden baseplate. In the center is a smaller inset showing a digital 3D rendering of the same model. On the right is a screenshot of a software interface, likely a game engine or simulation tool, displaying various parameters and a code editor window.

With Instant NGP, NeRFs train in seconds, and render at real time rates (30 fps or faster)

20 NVIDIA


22

# Multiresolution Hash Encoding


The diagram illustrates the Multiresolution Hash Encoding process. It starts with an input image  $X$  (a face) which is processed by a series of feature maps  $F$  and  $T$  at multiple resolutions. The feature maps  $F$  are shown as grids of colored squares (red and blue) with indices 0 through 7. The feature maps  $T$  are shown as grids of colored squares (red and blue) with indices 0 through 7. The output of the feature maps is a vector  $y$  (red and green bars) which is then processed by a neural network (represented by a series of circles) to produce the final output  $z$ . The vector  $y$  is also labeled as  $\xi$  (Remaining inputs).

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# Reducing compute-per-sample: learned hash grids (Instant NGP)



Elapsed training time: 0 seconds



©2021, et al, 2022, Instant Neural Graphics Primitives with a Multiresolution Hash Encoding

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### 3D Gaussian Splatting for Radiance Fields



© 97 (to 67 ms)  
VSync On

Kerbl et al. 23 <https://www.youtube.com/watch?v=1kXY43vZu08>

# NeRFs for Digital Twins

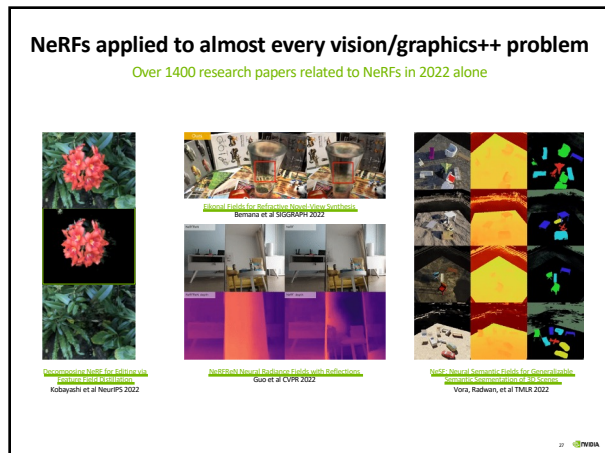




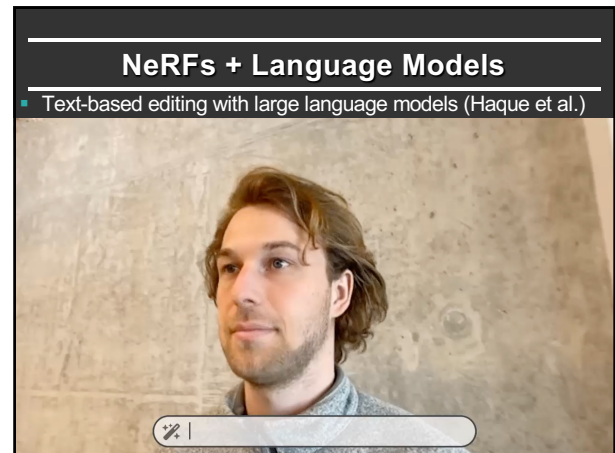
25



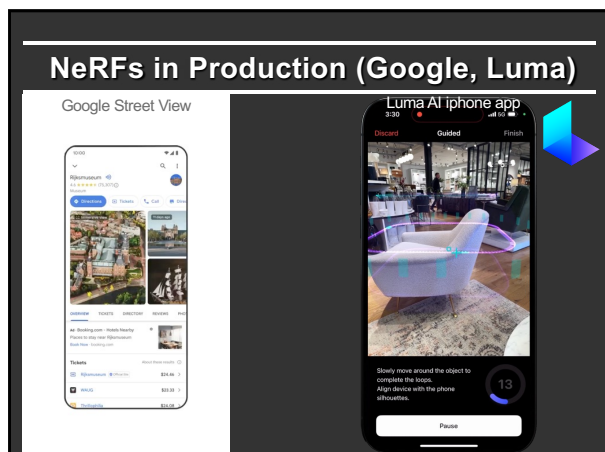
26



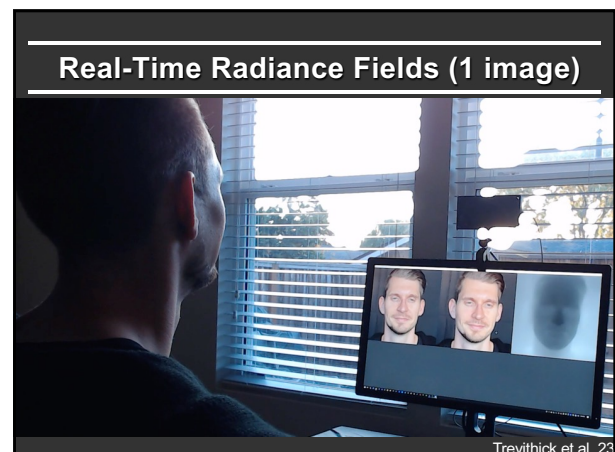
27



28



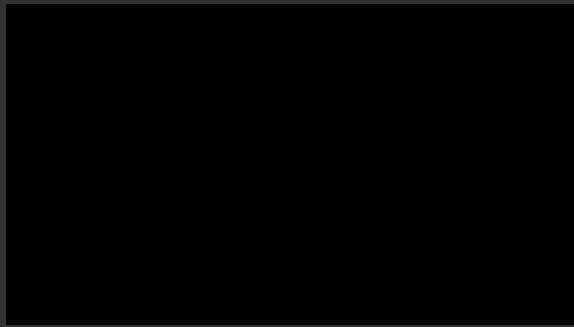
29



30



## Lifting Text-Based Avatars to 3D



31

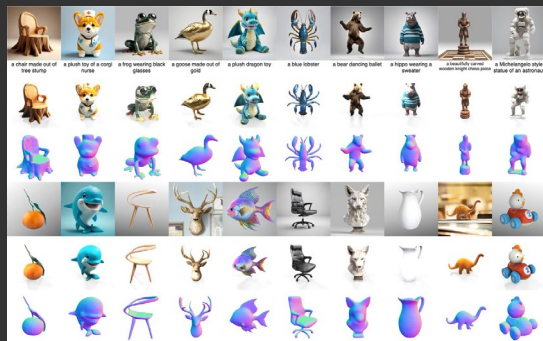
## 3D Videoconferencing



SIGGRAPH 23 Emerging Technologies

32

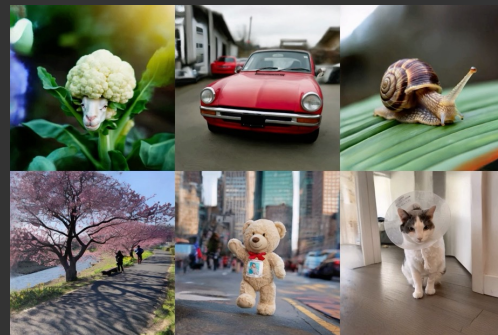
## Modern Text-Conditioned Diffusion (One-2-3-45++)



Liu et al. 24

33

## CAT3D: Create Anything in 3D



Gao et al. 24. See also <https://www.youtube.com/watch?v=ZKUcowfFDPk>

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## Stochastic Geometry: Objects as Volumes

- Volumetric rendering is great, but what if you want an actual 3D representation?
- Possible with stochastic view of geometry, unifies objects with hard surfaces and volumes (Miller et al. CVPR 24)
- <https://www.youtube.com/watch?v=ZKUcowfFDPk>

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