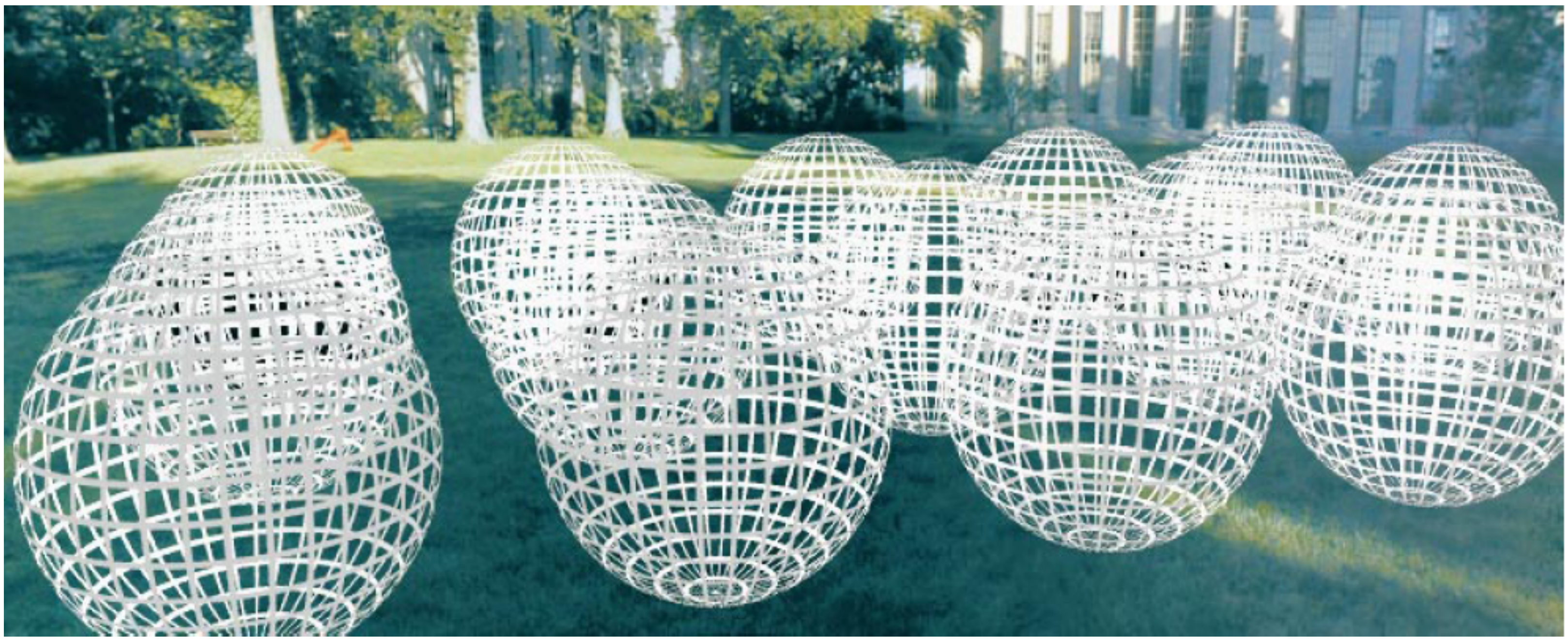
Modeling the plenoptic function



Adopted from: CS194: Intro to Comp. Vision, and Comp. Photo
Alexei Efros & Angjoo Kanazawa, UC Berkeley, Fall 2021

Outline

- The plenoptic function
- Two-plane light fields
- Plenoptic camera
- Neural radiance fields (NeRFs)

Goal: Novel view rendering

- Given several images of the same object or scene from known viewpoints, how can we generate a rendering of the same scene from a novel viewpoint?
- Multiview stereo answer: create a textured 3D model from the images, use traditional graphics to render

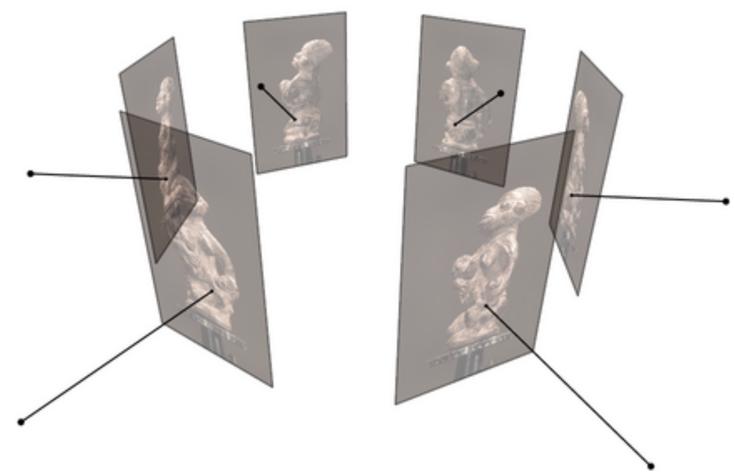
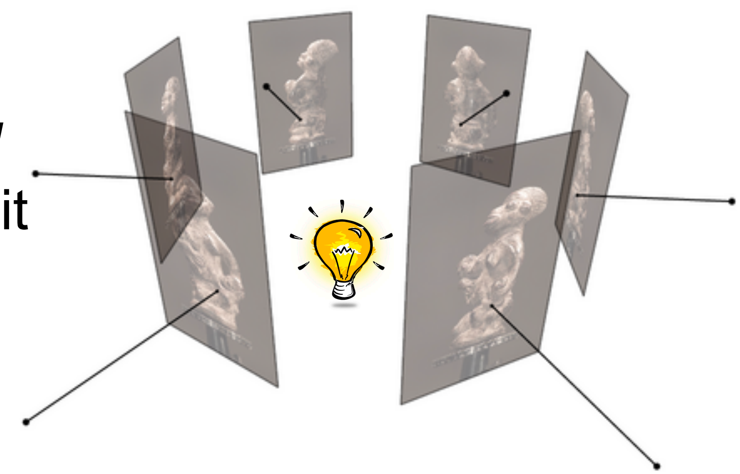


Figure source: C. Hernandez, N. Snavely

Goal: Novel view rendering

- Given several images of the same object or scene from known viewpoints, how can we generate a rendering of the same scene from a novel viewpoint?
- Multiview stereo answer: create a textured 3D model from the images, use traditional graphics to render
- Alternate answer: model the *light field* of the scene, sample new views from it



The light field, or plenoptic function

Figure by Leonard McMillan

Q: What is the set of all things that we can ever see?

A: The *plenoptic function*

E. Adelson and J. Bergen. The plenoptic function and the elements of early vision. Computational models of visual processing, MIT Press, 1991

The light field, or plenoptic function

Figure by Leonard McMillan

Q: What is the set of all things that we can ever see?

A: The *plenoptic function*

Let's start with a stationary person and try to parameterize everything that they can see…

Grayscale snapshot

$L(\theta, \phi)$

- Intensity of light
  - Seen from a single view point
  - At a single time
  - Averaged over the wavelengths of the visible spectrum

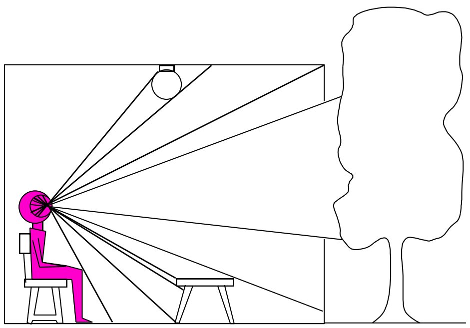
Color snapshot

$L(\theta, \phi, \lambda)$

- Intensity of light
  - Seen from a single view point
  - At a single time
  - As a function of wavelength

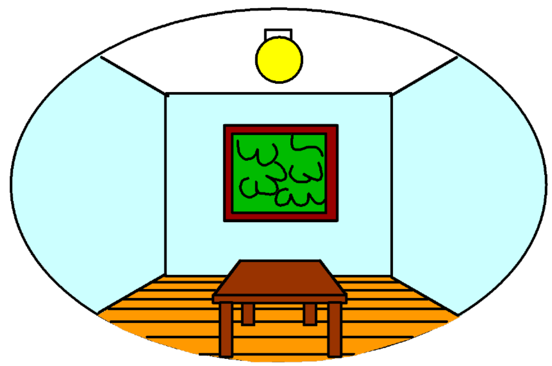
Modeling the light field

3D world



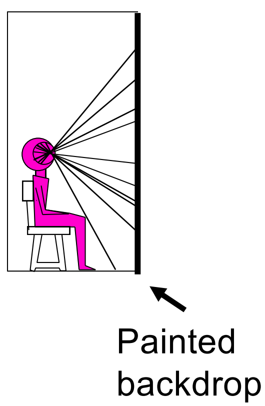
Point of observation

2D image

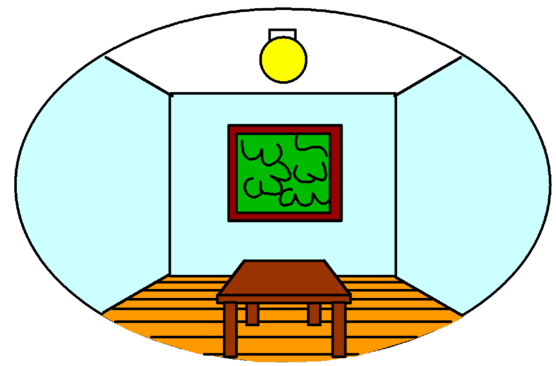


Modeling the light field

3D world



2D image

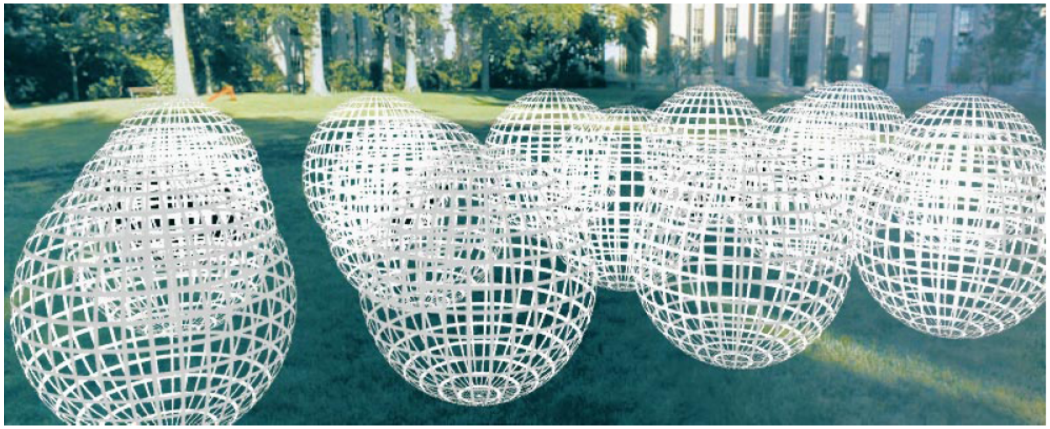


A movie

$$L(\theta, \phi, \lambda, t)$$

- Intensity of light
  - Seen from a single view point
  - Over time
  - As a function of wavelength

Holographic movie



$L(\theta, \phi, \lambda, t, x, y, z)$

- Intensity of light
  - Seen from ANY viewpoint
  - Over time
  - As a function of wavelength

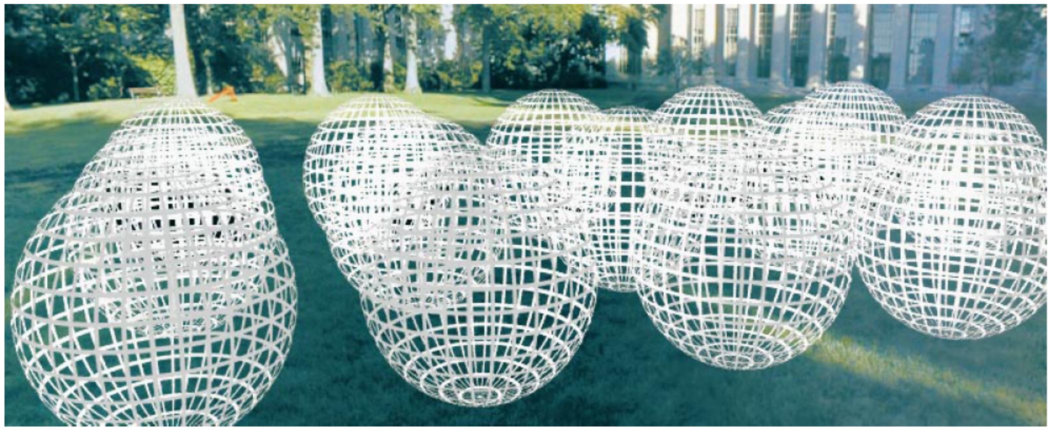
End-of-semester deadlines

- **Quiz 4** will be out 9AM **Thursday, December 1st** through 9AM **Monday, December 5th**
- **Assignment 5** is out, due **Tuesday, December 6**
- **Extra credit project presentations** will take place on **Monday, December 5th** and **Wednesday, December 7th** *please sign up by next Tuesday!*
- Final project reports will be due on **Monday, December 12th**

Light field modeling: Outline

- The plenoptic function
- Two-plane light fields
- Plenoptic camera
- Neural radiance fields (NeRFs)

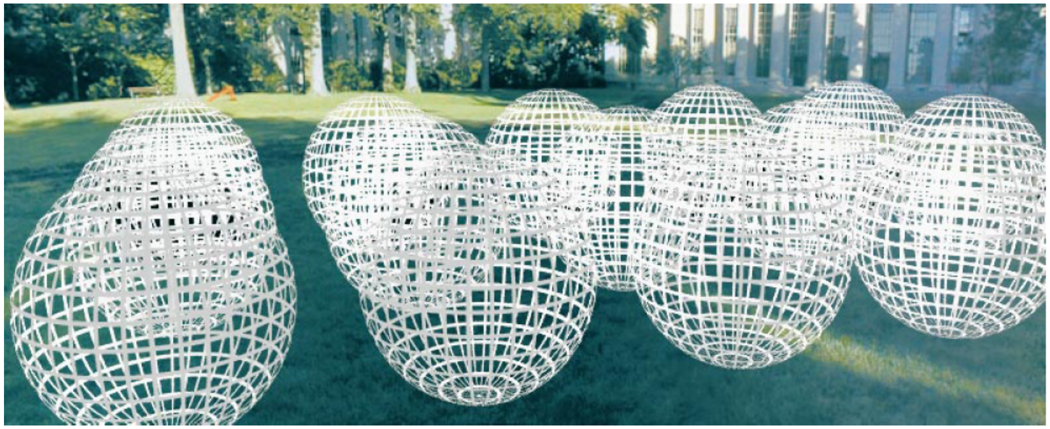
The plenoptic function



$$L(\theta, \phi, \lambda, t, x, y, z)$$

- Can reconstruct every possible view, at every moment, from every position, at every wavelength
- Contains every photograph, every movie, everything that anyone has ever seen! it completely captures our visual reality!
- Not bad for a function…

The plenoptic function: More practical version



$$L(\theta, \phi, x, y, z) = (r, g, b)$$

- Other simplifications/variants are possible, as we will see

Modeling the plenoptic function

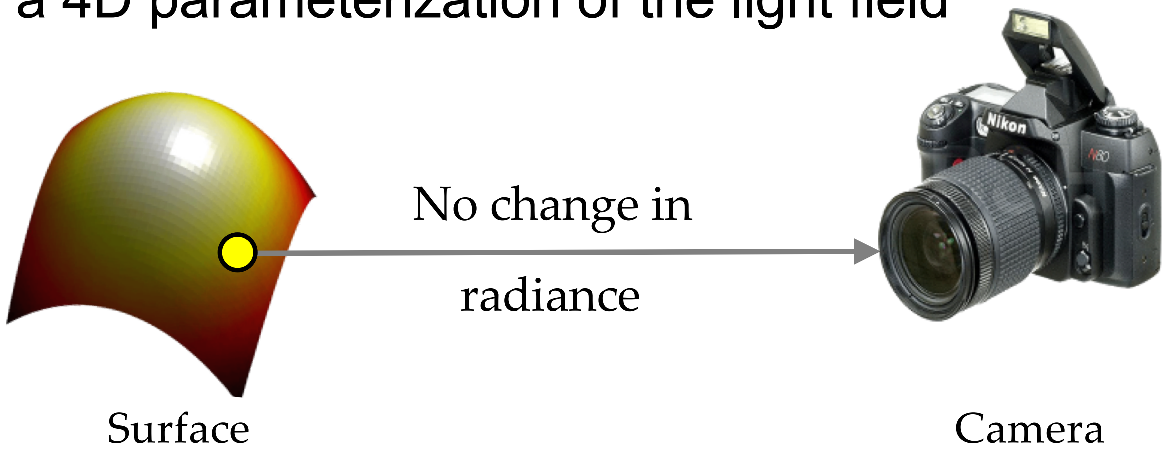
- Capture
  - Create a special camera setup to capture a slice of the plenoptic function
  - Combine captured rays for novel view synthesis, defocus, and other effects
- Optimization
  - Given a set of multi-view calibrated images, optimize a parametric representation of the plenoptic function of the scene

Outline

- The plenoptic function
- Two-plane light fields

Two-plane light fields

- Key idea: assuming light is constant along rays, we can create a 4D parameterization of the light field



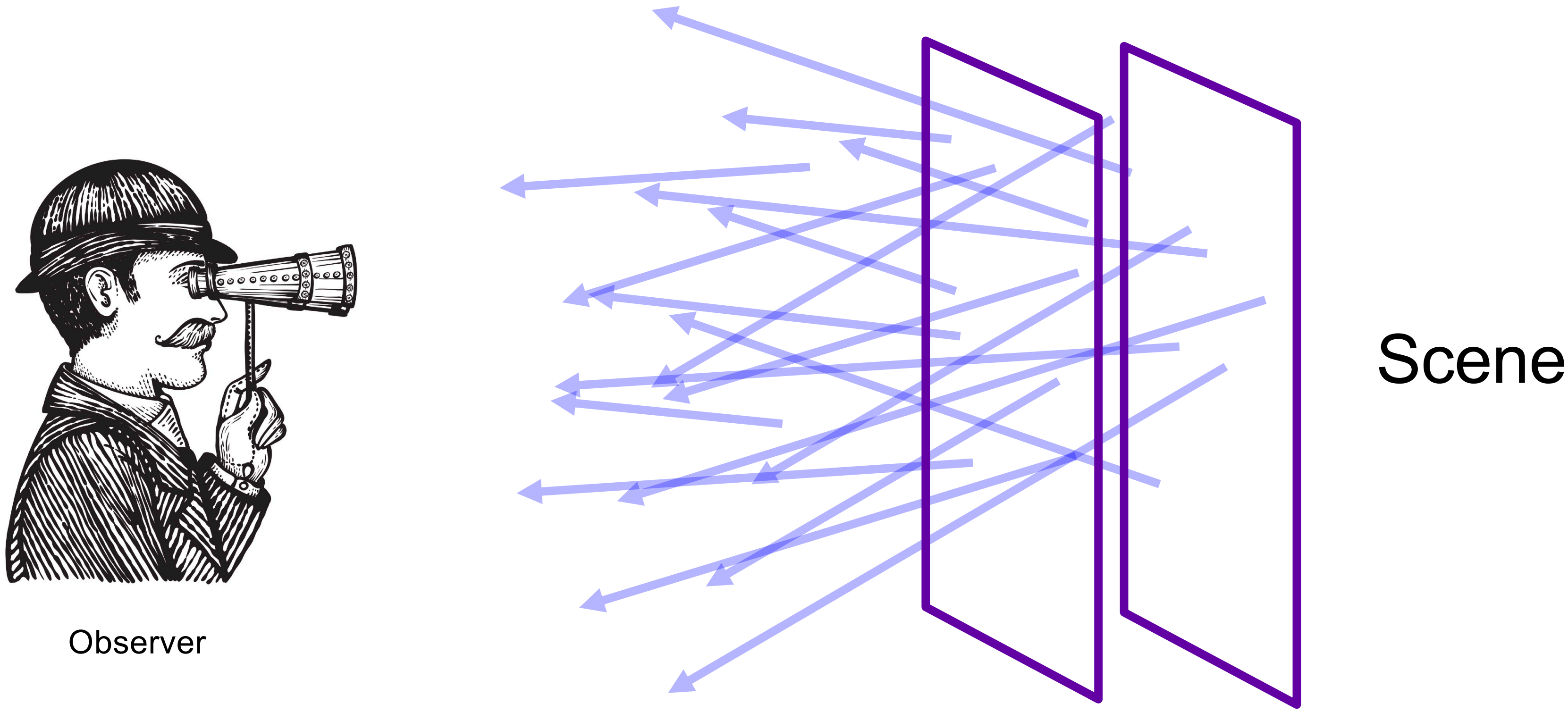
If there is no occlusion or fog

S. Gortler, R. Grzeszczuk, S. Szeliski, M. Cohen. The Lumigraph. Proceedings of the 23rd Annual Conference on Computer Graphics and Interactive Techniques, 1996

M. Levoy and P. Hanrahan. Light field rendering. SIGGRAPH 1996

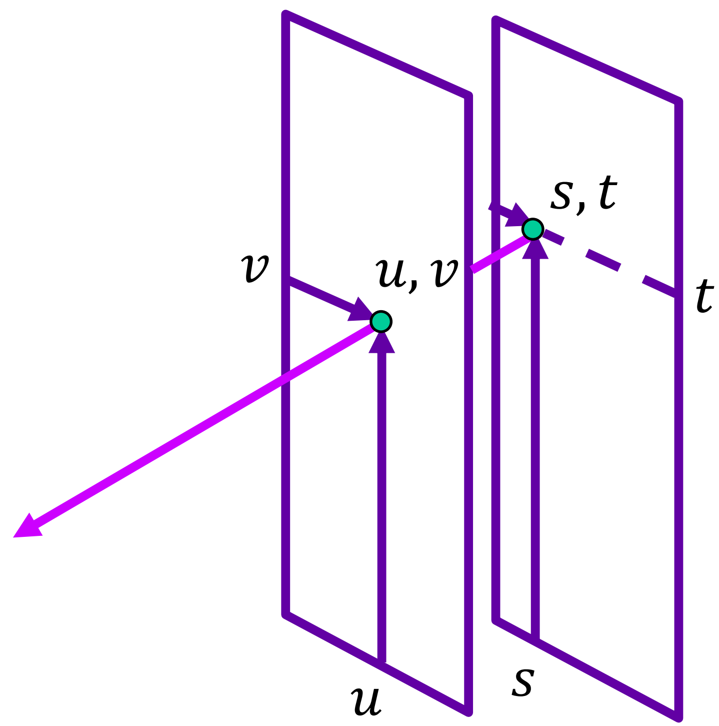
Two-plane light fields

- Two-plane parameterization:



Two-plane light fields

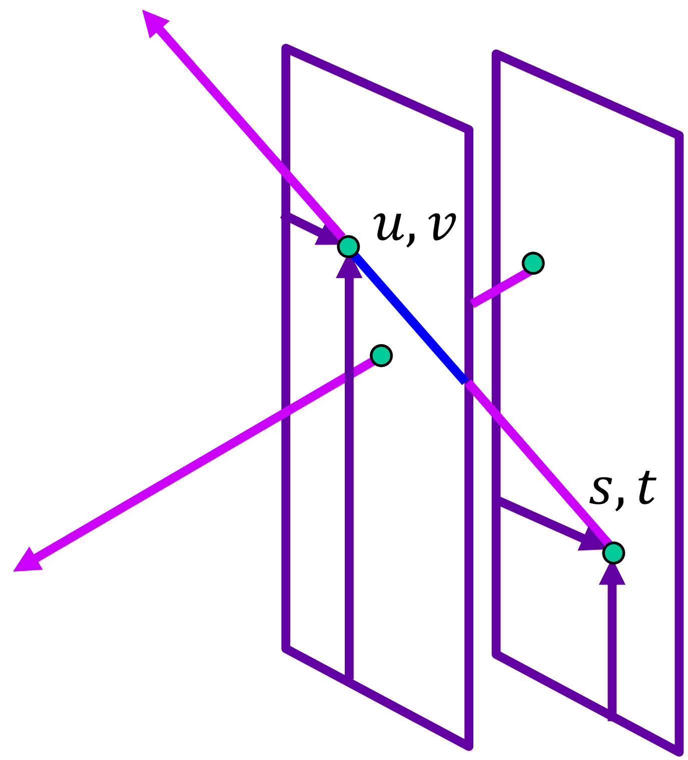
- Two-plane parameterization:



$$L(s,t,u,v) = (r,g,b)$$

Two-plane light fields

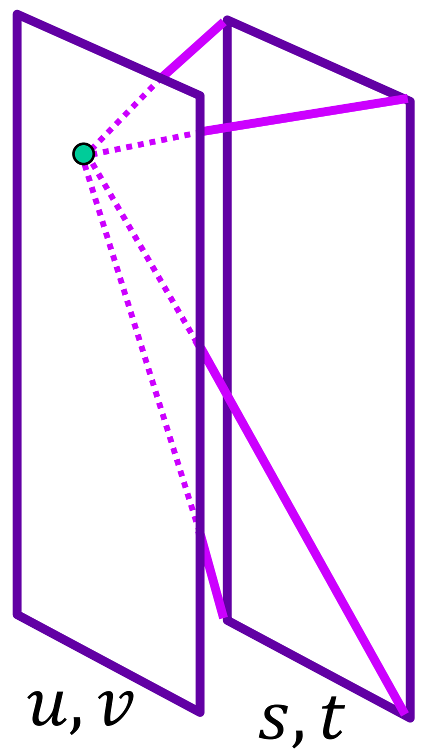
- Two-plane parameterization:



$$L(s,t,u,v) = (r,g,b)$$

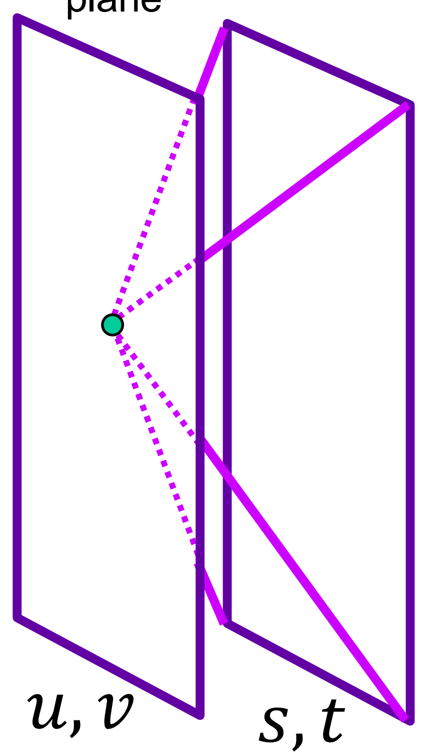
Two-plane light fields

- What do we get if we hold u, v constant and let s, t vary?
- An image!



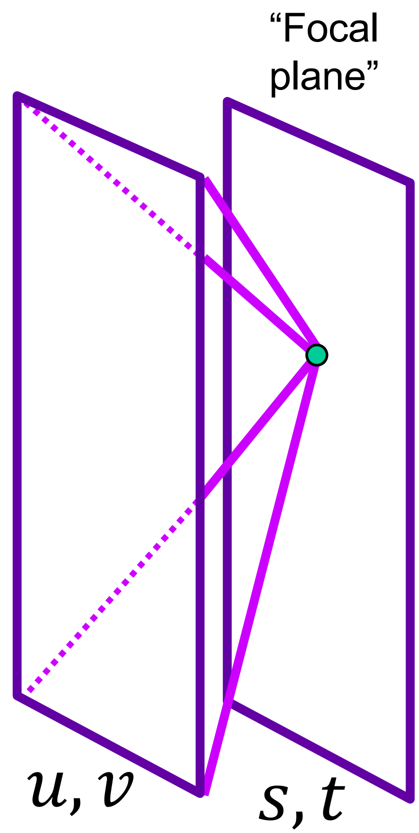
Two-plane light fields

- What do we get if we hold u, v constant and let s, t vary?
- An image!



Two-plane light fields

- What do we get if we hold s, t constant and let u, v vary?
- A set of rays leaving a point in the scene in a bundle of directions towards the image plane



Light field visualization

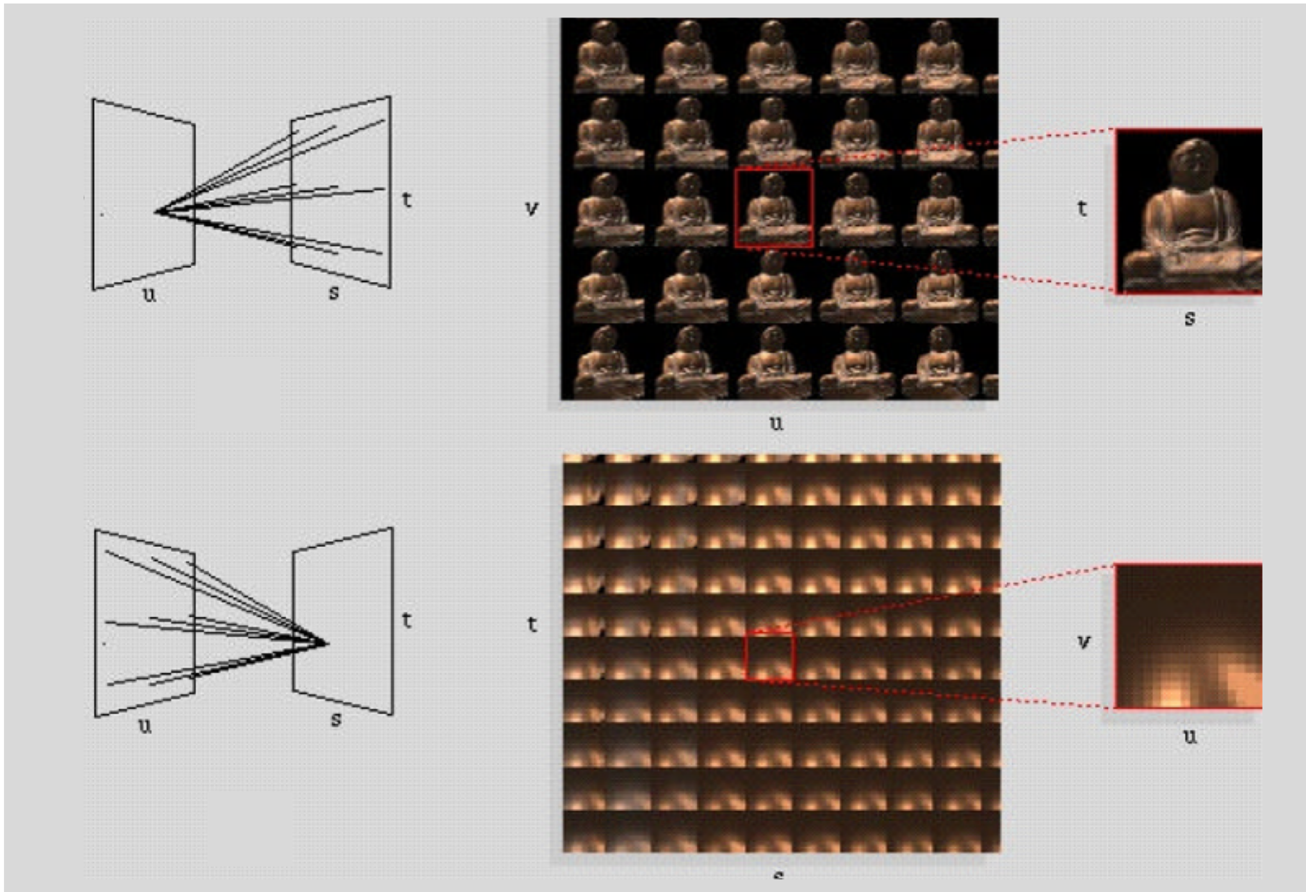
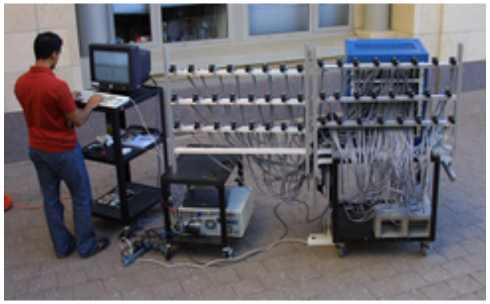
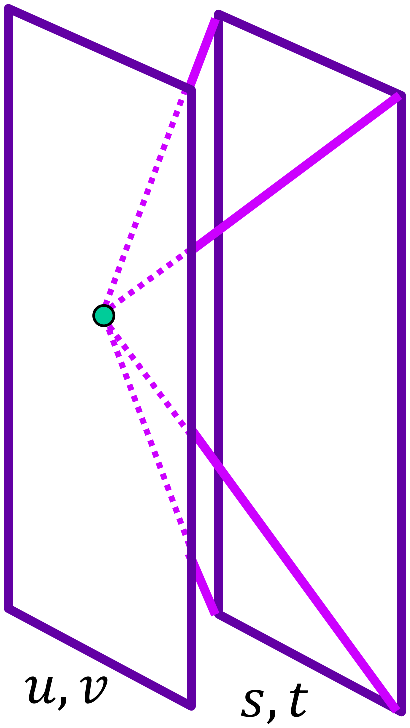


Figure source: M. Levoy and P. Hanrahan

Light field capture

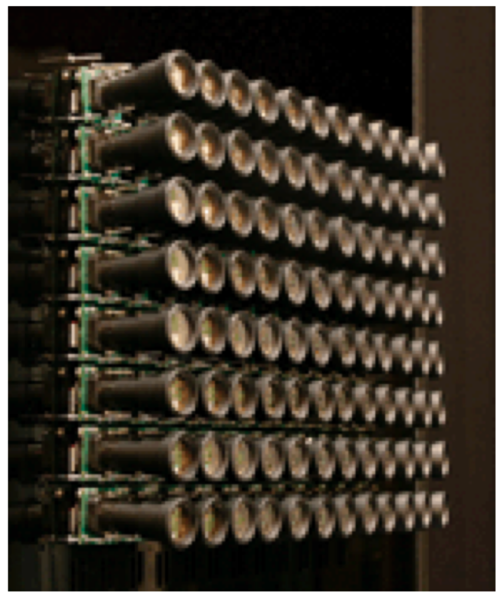
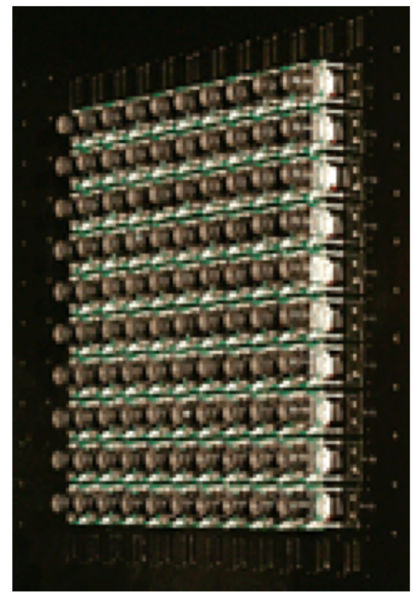
- Idea 1: move camera carefully over u, v plane





Stanford multi-camera array

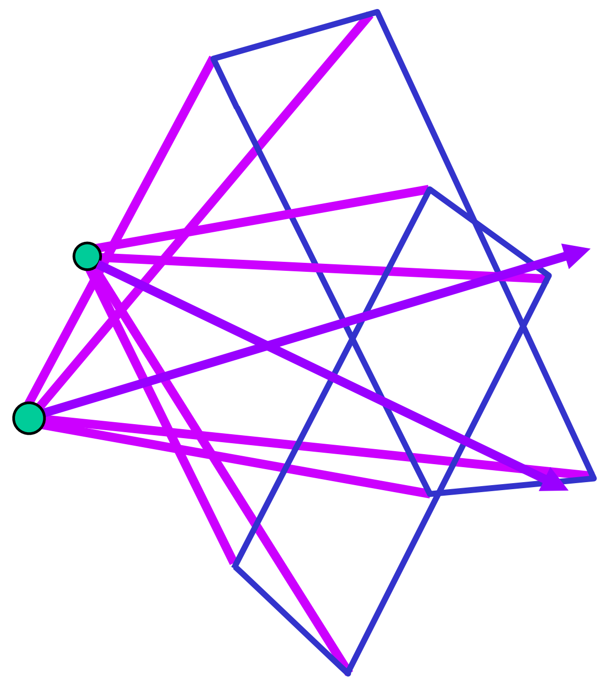
- 640 × 480 pixels ×
  30 fps × 128 cameras
- Synchronized timing
- Continuous streaming
- Flexible arrangement

http://graphics.stanford.edu/projects/array/

Light field capture

- Idea 2: move camera anywhere, use rebinning or resampling



Light field capture

- Idea 2: move camera anywhere, use rebinning or resampling

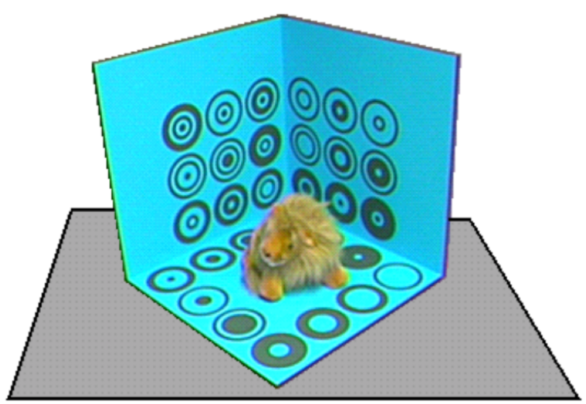
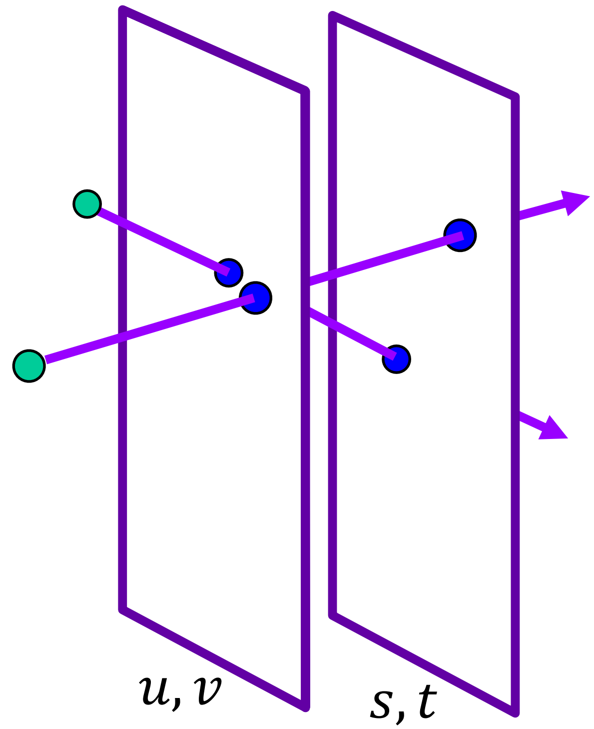


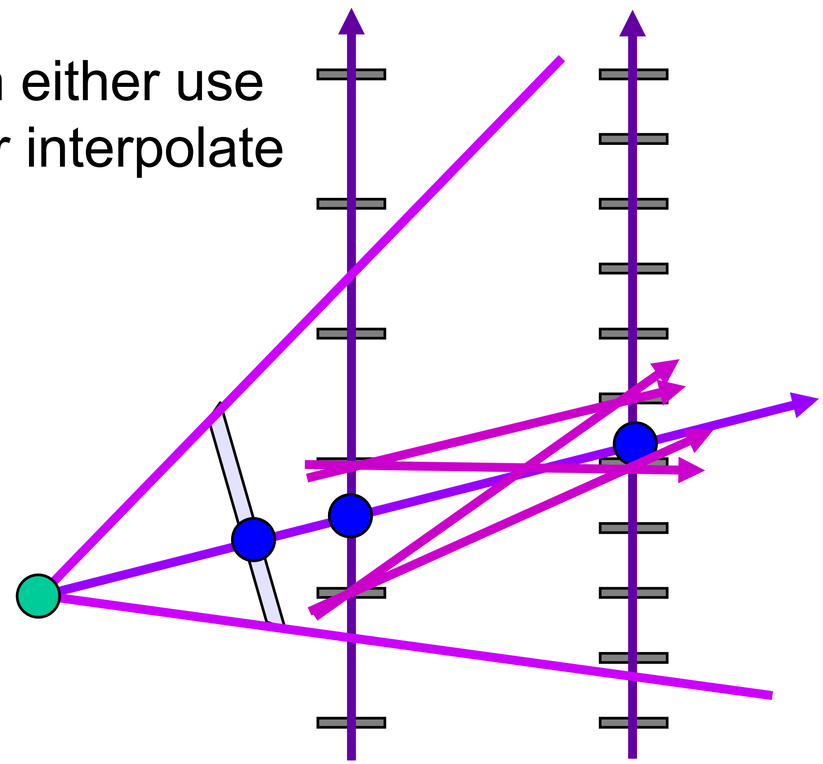
Figure 10: The capture stage

Figure source: S. Gortler et al.



Novel view synthesis

- For each output pixel, determine s, t, u, v, then either use closest discrete RGB or interpolate several nearby values



Slide by Rick Szeliski and Michael Cohen

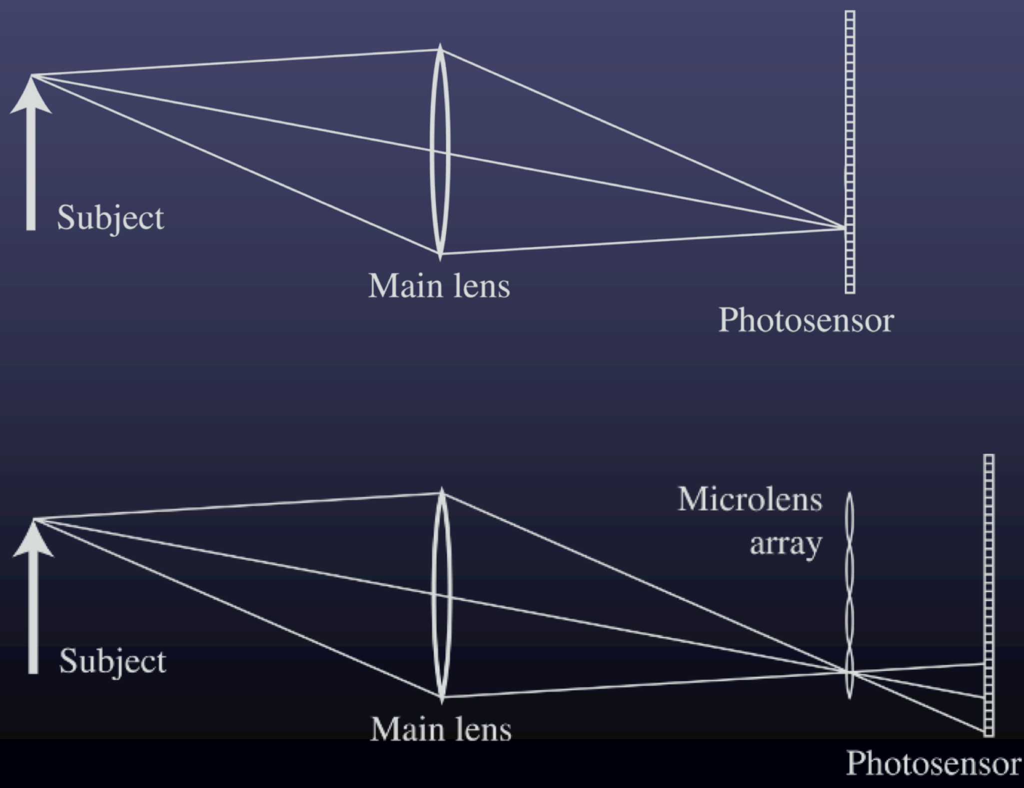
Outline

- The plenoptic function
- Two-plane light fields
- Plenoptic camera

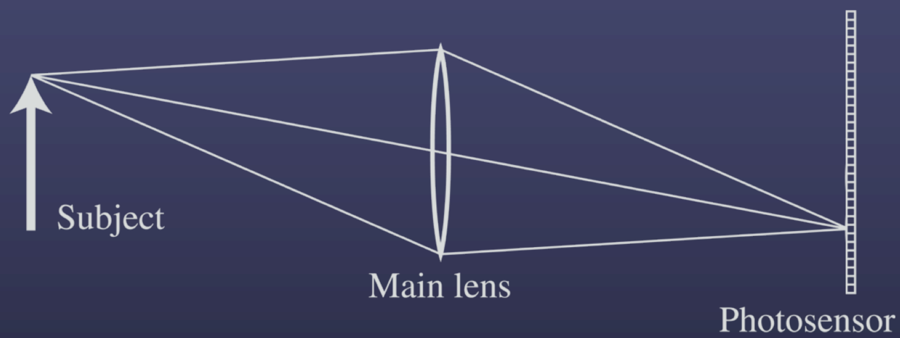
Plenoptic camera

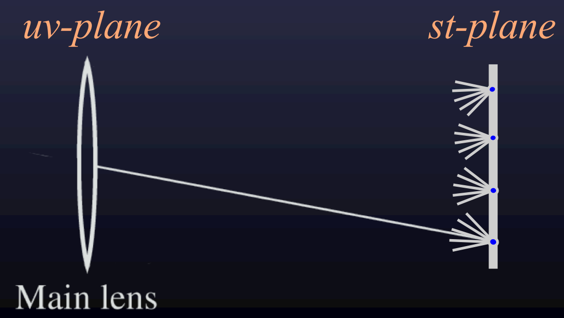
R. Ng et al. Light Field Photography with a Hand-held Plenoptic Camera. 2005

Conventional vs. light field camera



Conventional vs. light field camera



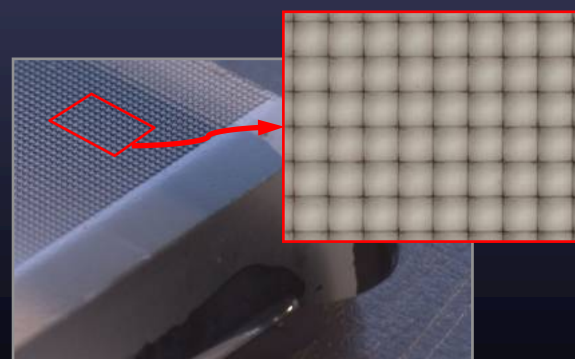


Prototype camera

Contax medium format camera

Kodak 16-megapixel sensor

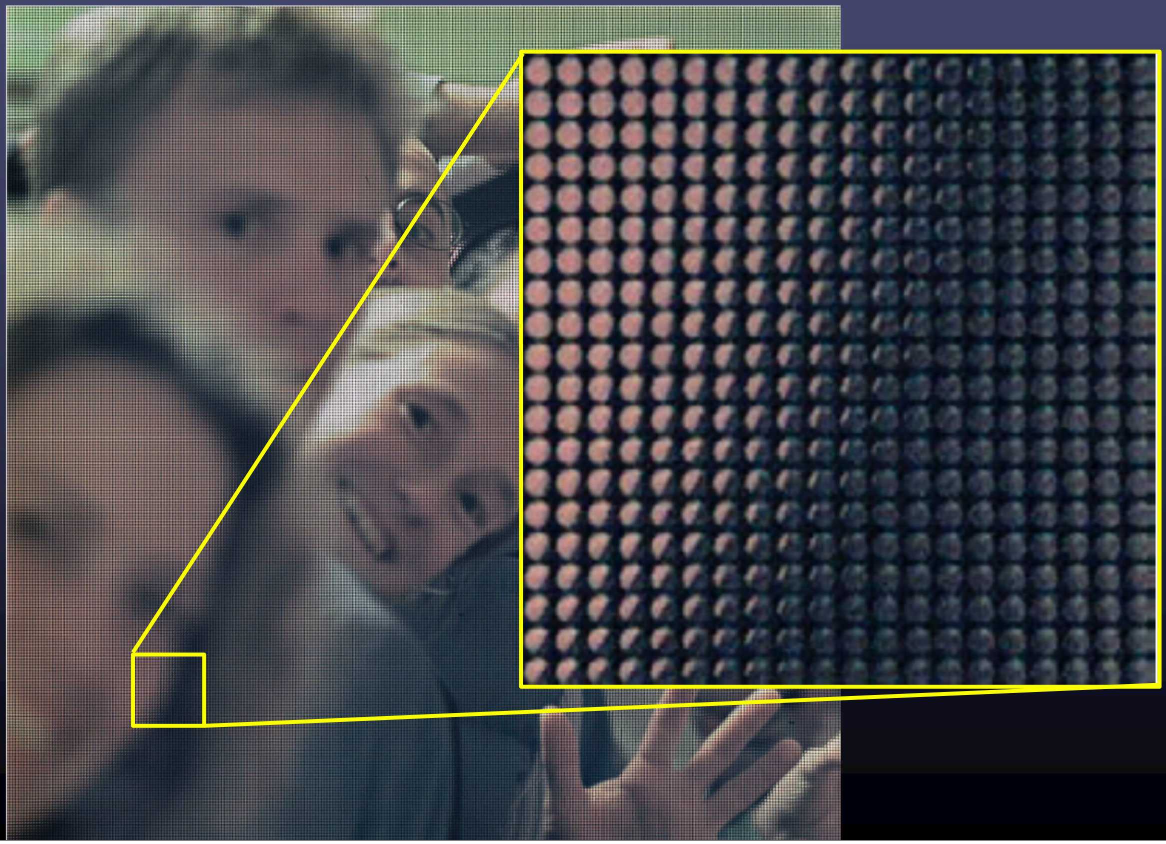
Adaptive Optics microlens array



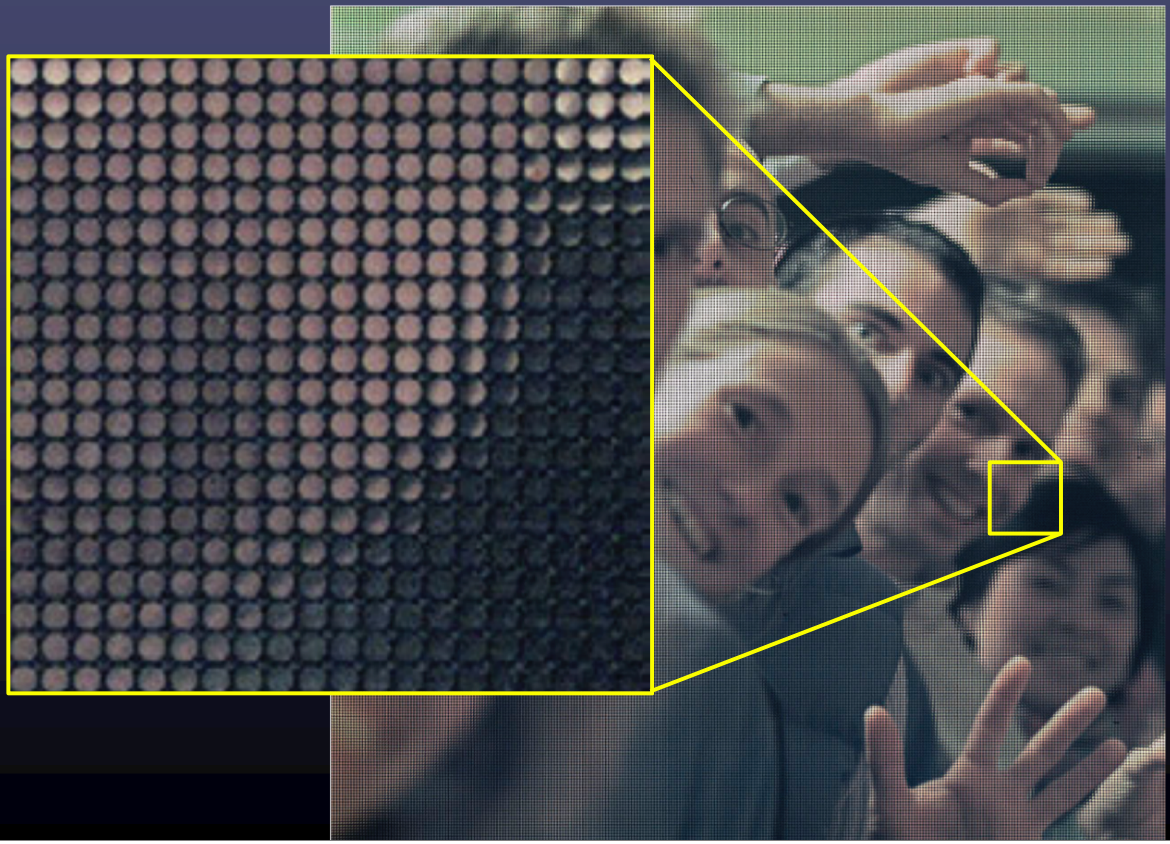
125μ square-sided microlenses

4000 × 4000 pixels / 292 × 292 lenses = 14 × 14 pixels per lens

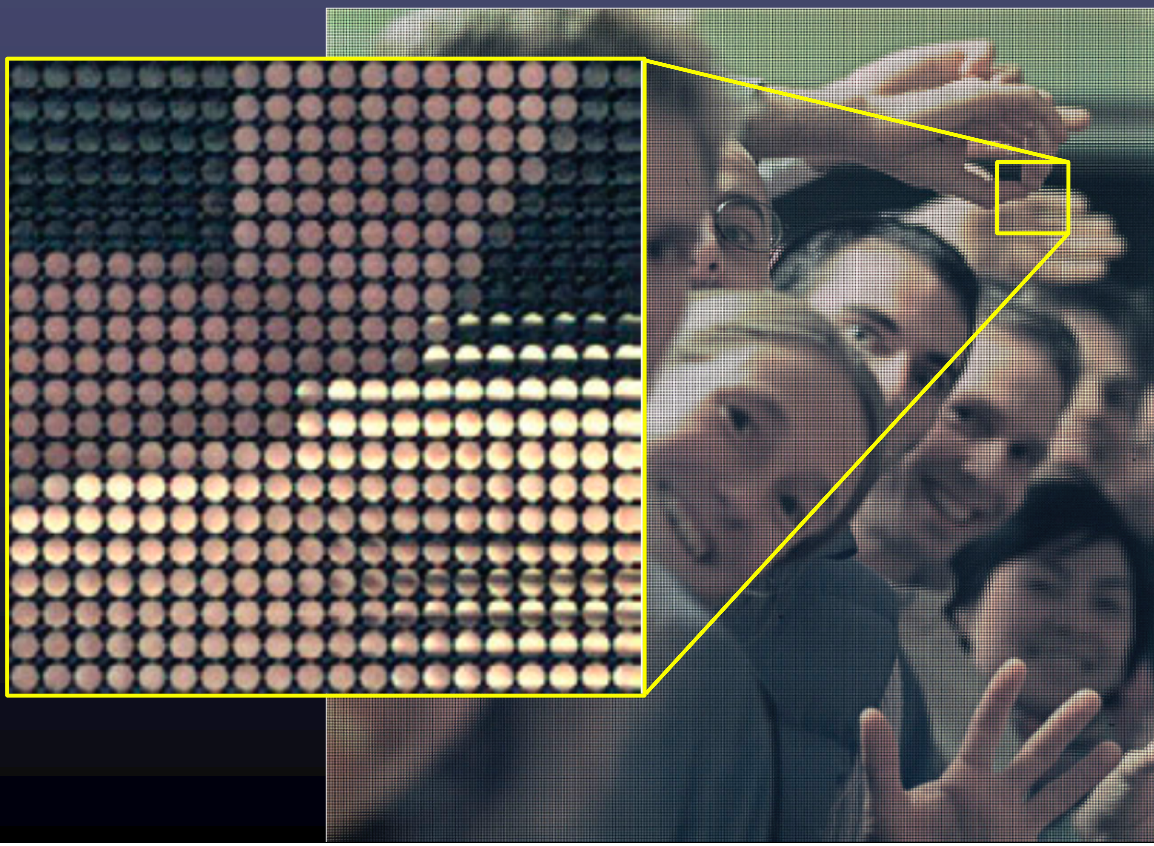
Captured light field



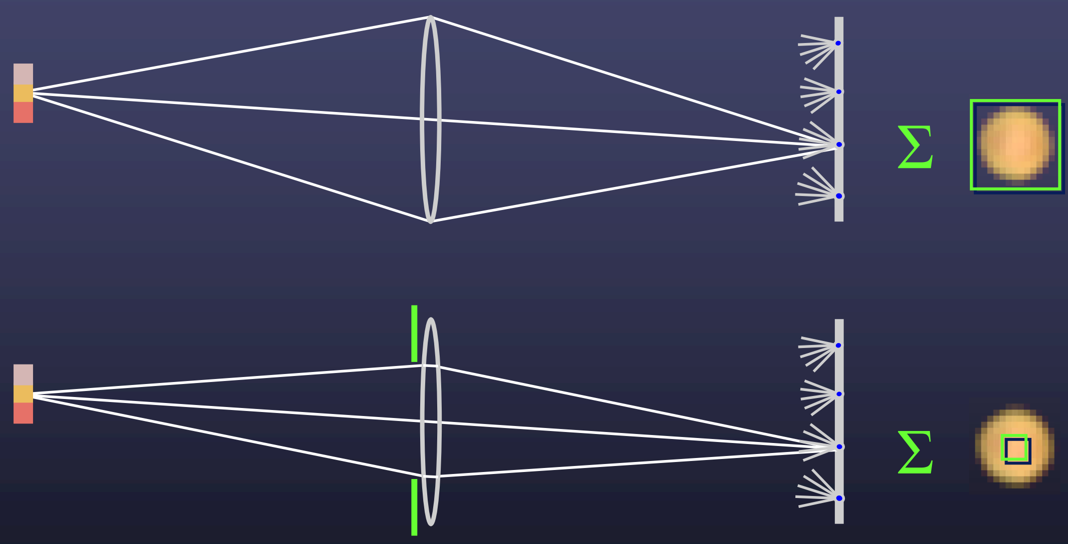
Captured light field



Captured light field

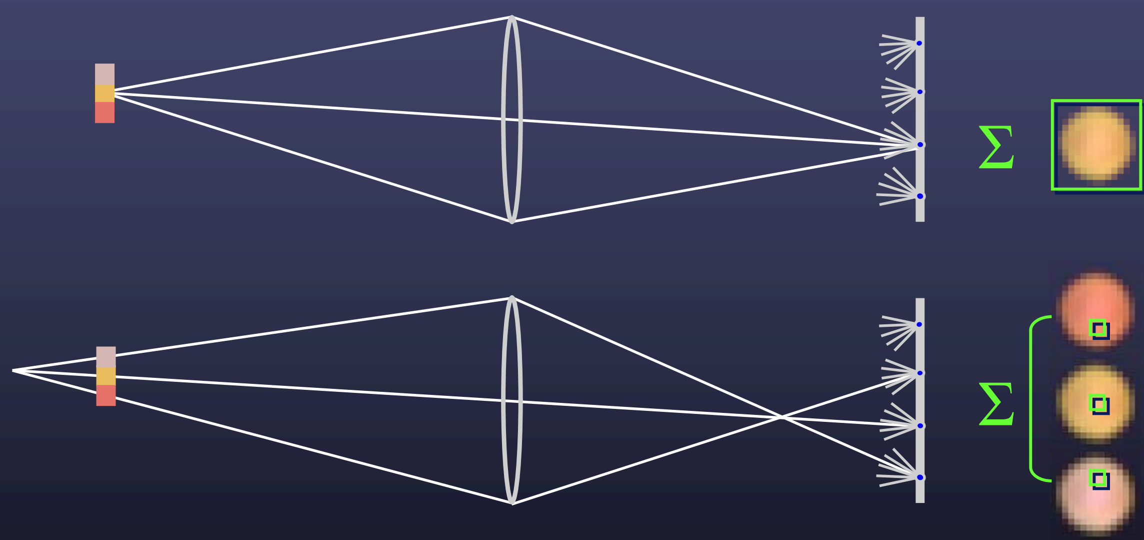


Digitally stopping down (reducing the aperture)



- stopping down = summing only the central portion of each microlens

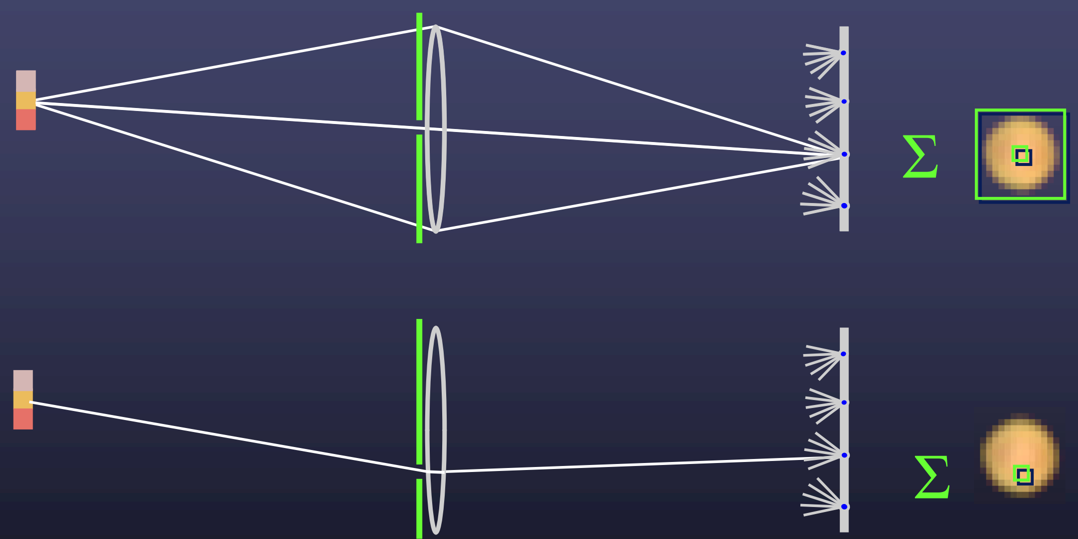
Digital refocusing



- refocusing = summing windows extracted from several microlenses

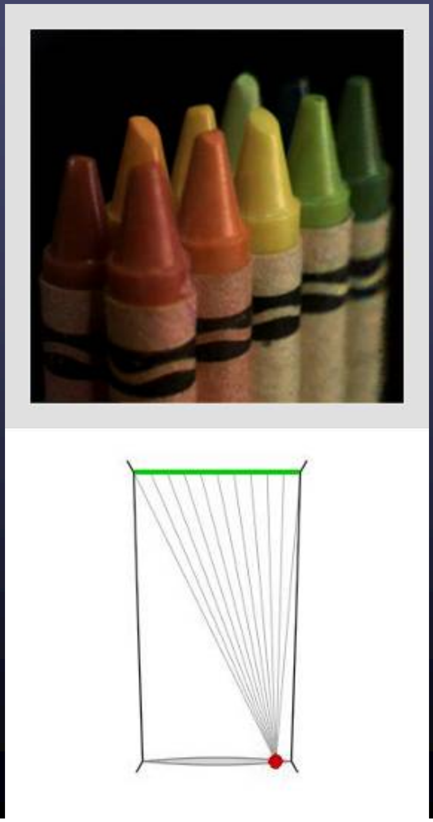
Digital refocusing

Digitally moving the observer

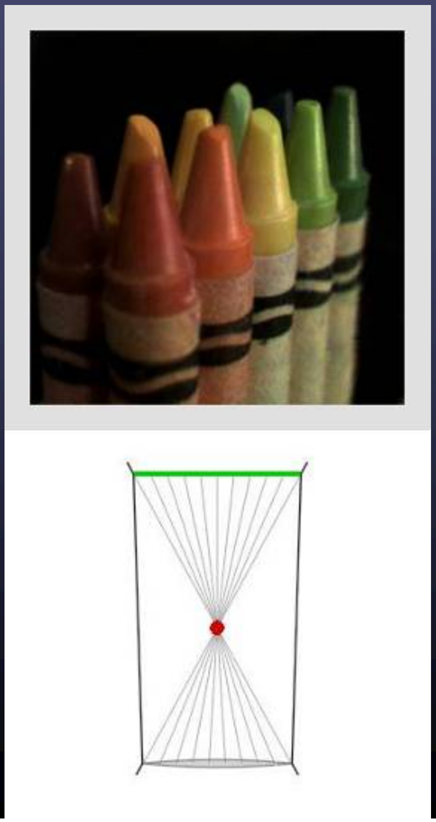


- moving the observer = moving the window we extract from the microlenses

Digitally moving the observer



Digitally moving the observer



Lytro (RIP)

https://en.wikipedia.org/wiki/Lytro

What happened to Lytro?

Outline

- The plenoptic function
- Two-plane light fields
- Plenoptic camera
- Neural radiance fields (NeRFs)

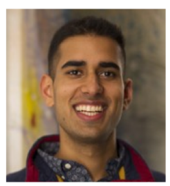
NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis

ECCV 2020 (best paper honorable mention)

Ben Mildenhall*

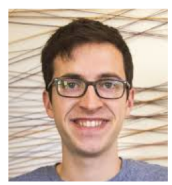
UC Berkeley

Pratul Srinivasan*



UC Berkeley

Matt Tancik*



UC Berkeley

Jon Barron

Google Research

Ravi Ramamoorthi

UC San Diego

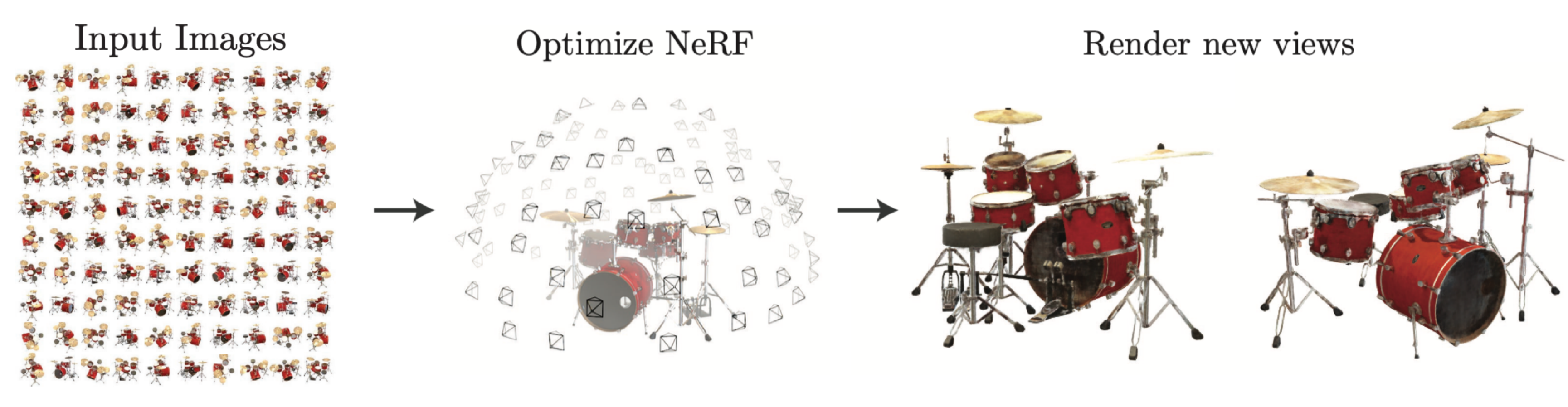
Ren Ng

UC Berkeley

https://www.matthewtancik.com/nerf

NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis

ECCV 2020 (best paper honorable mention)



Train a neural network to represent the plenoptic function

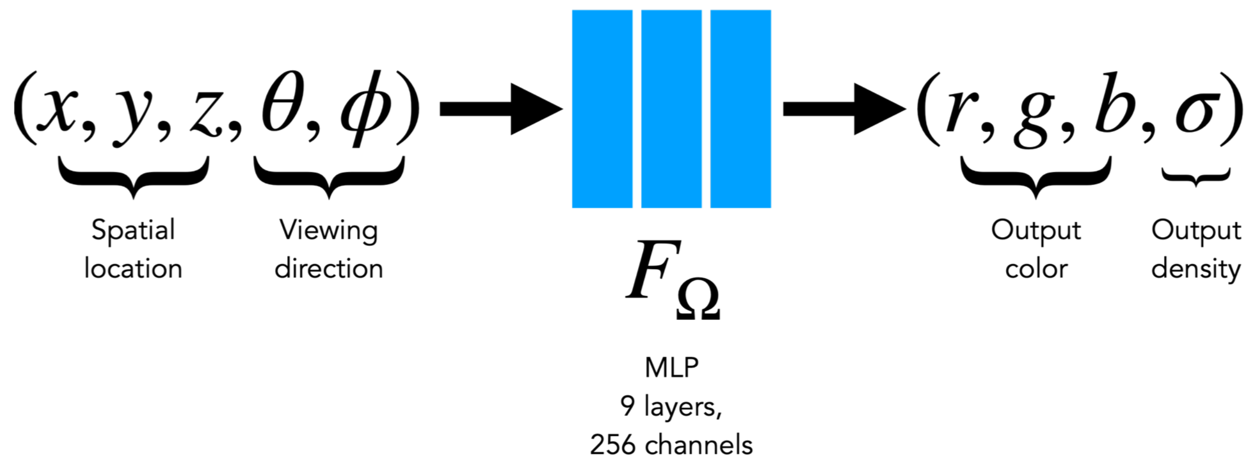
Inputs: sparsely sampled images of scene

Outputs: *new* views of same scene

tancik.com/nerf

Slide credit: Jon Barron

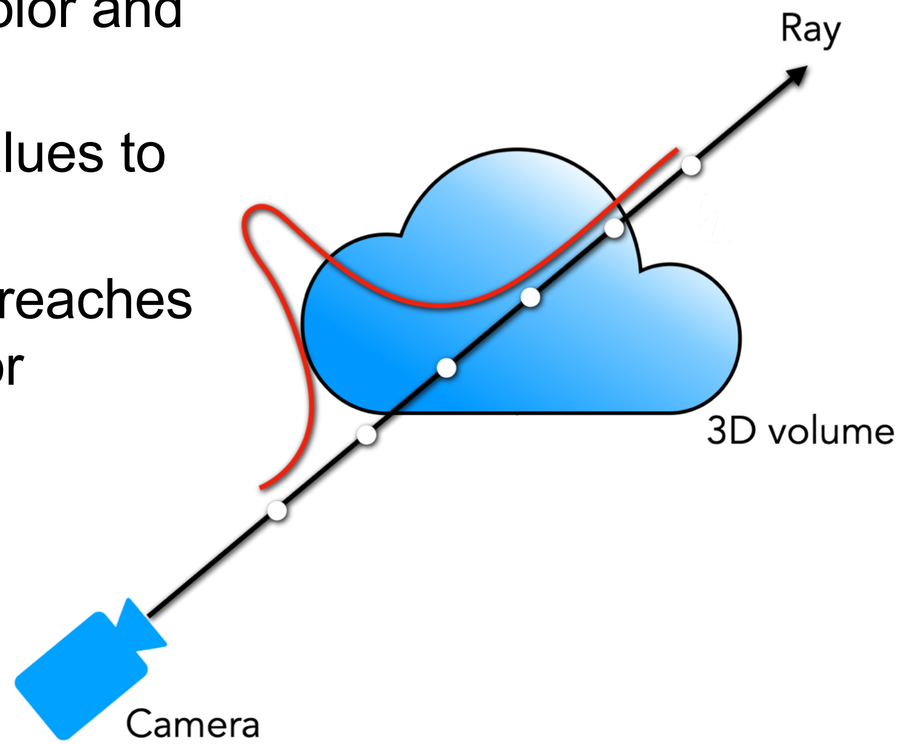
Neural radiance field



Volumetric “fog” model: Every 5D input gets mapped to **Color** and **Density**

NeRF rendering

- At every point you know color and density: (c_i, σ_i)
- Need to integrate these values to render a pixel
- Idea: sum how much light reaches each point * visibility * color



How to render a pixel: Volume rendering

Given: a ray $\mathbf{r}(i) = \vec{o} + i\vec{d}$ At every point you know: (c_i, σ_i)

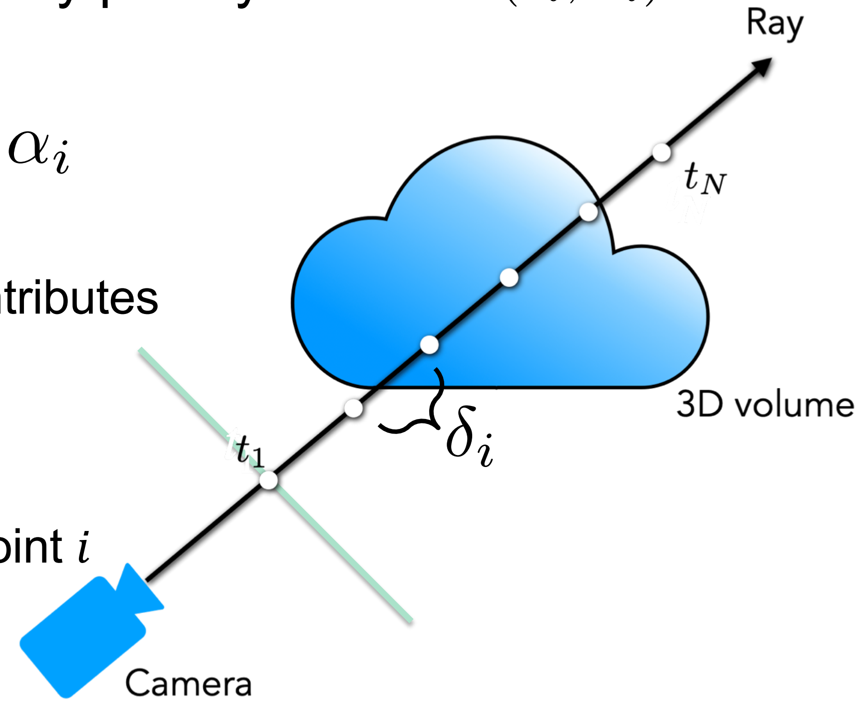
$$C(\mathbf{r}) \approx \sum_{i}^{N} w_i c_i \qquad w_i = T_i \alpha_i$$

Alpha: How much light a ray segment contributes

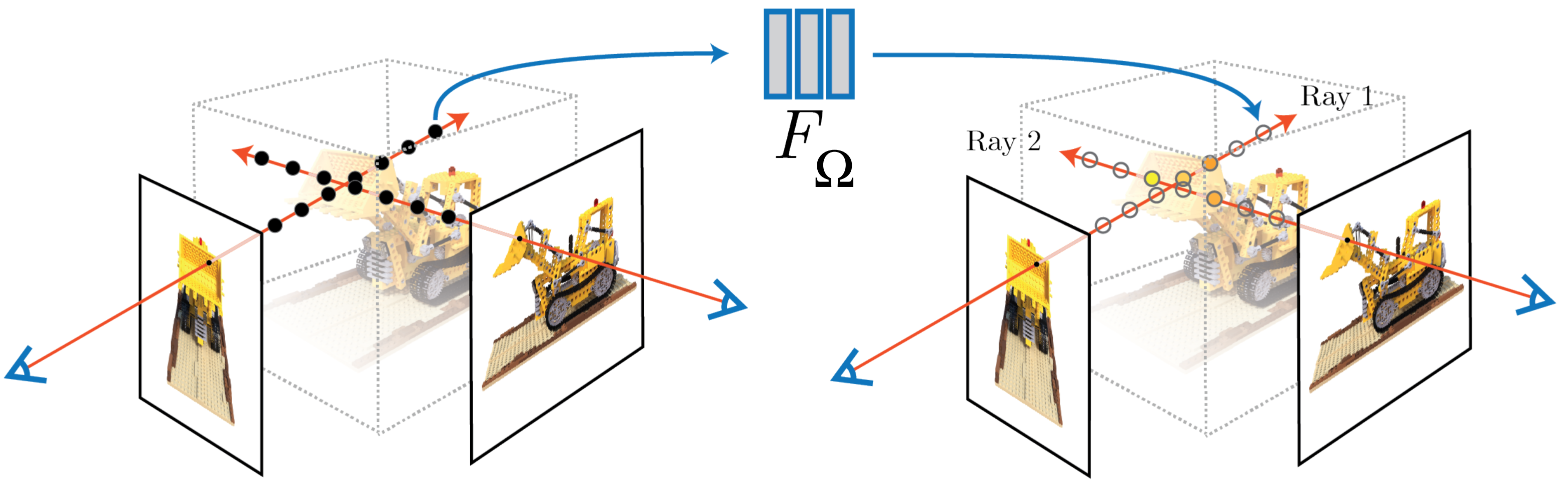
$$\alpha_i = 1 - \exp(-\sigma_i \delta_i)$$

Transmittance: how much light reaches point i

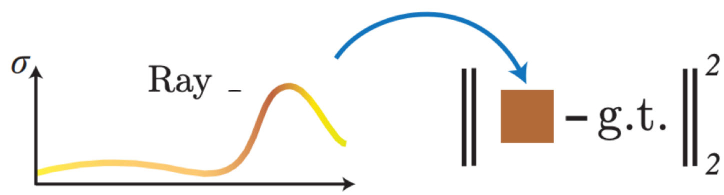
$$T_i = \prod_{j=1}^{i-1} (1 - \alpha_j)$$



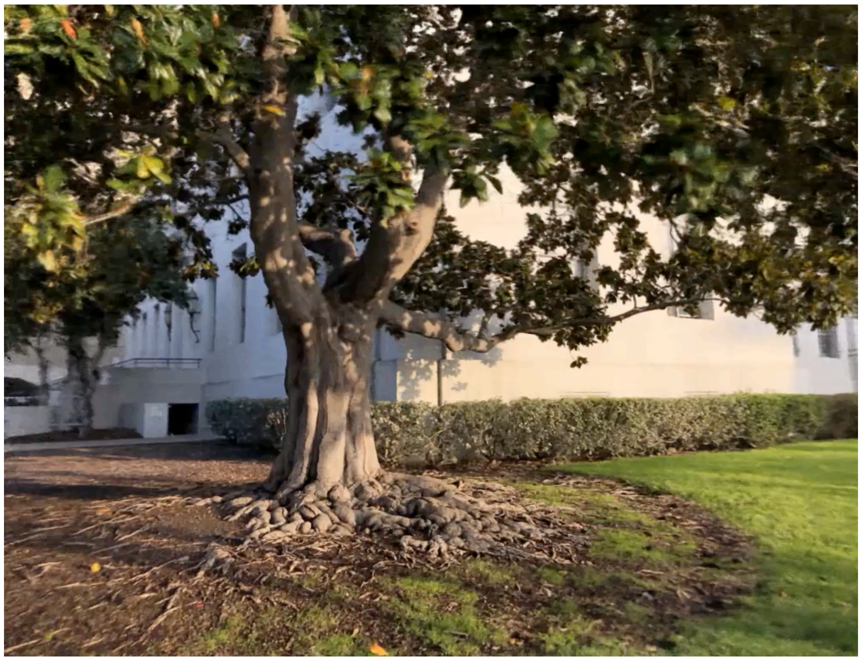
Training: Optimization with reconstruction loss

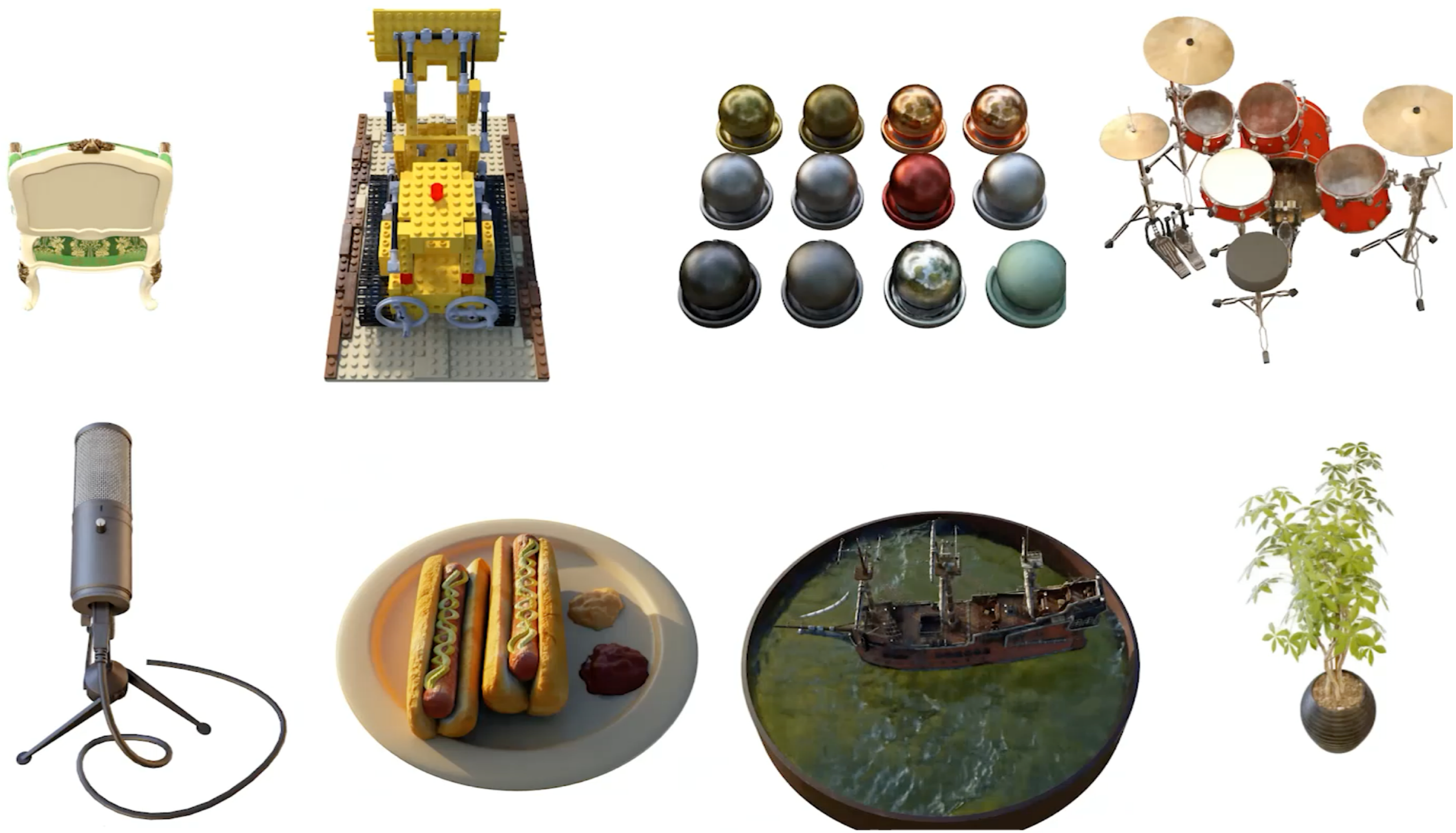


$$\min_{\Omega} \sum_{i} \|\text{render}^{(i)}(F_\Omega) - I_{\text{gt}}^{(i)}\|^2$$



Example results





Viewpoint-dependent effects

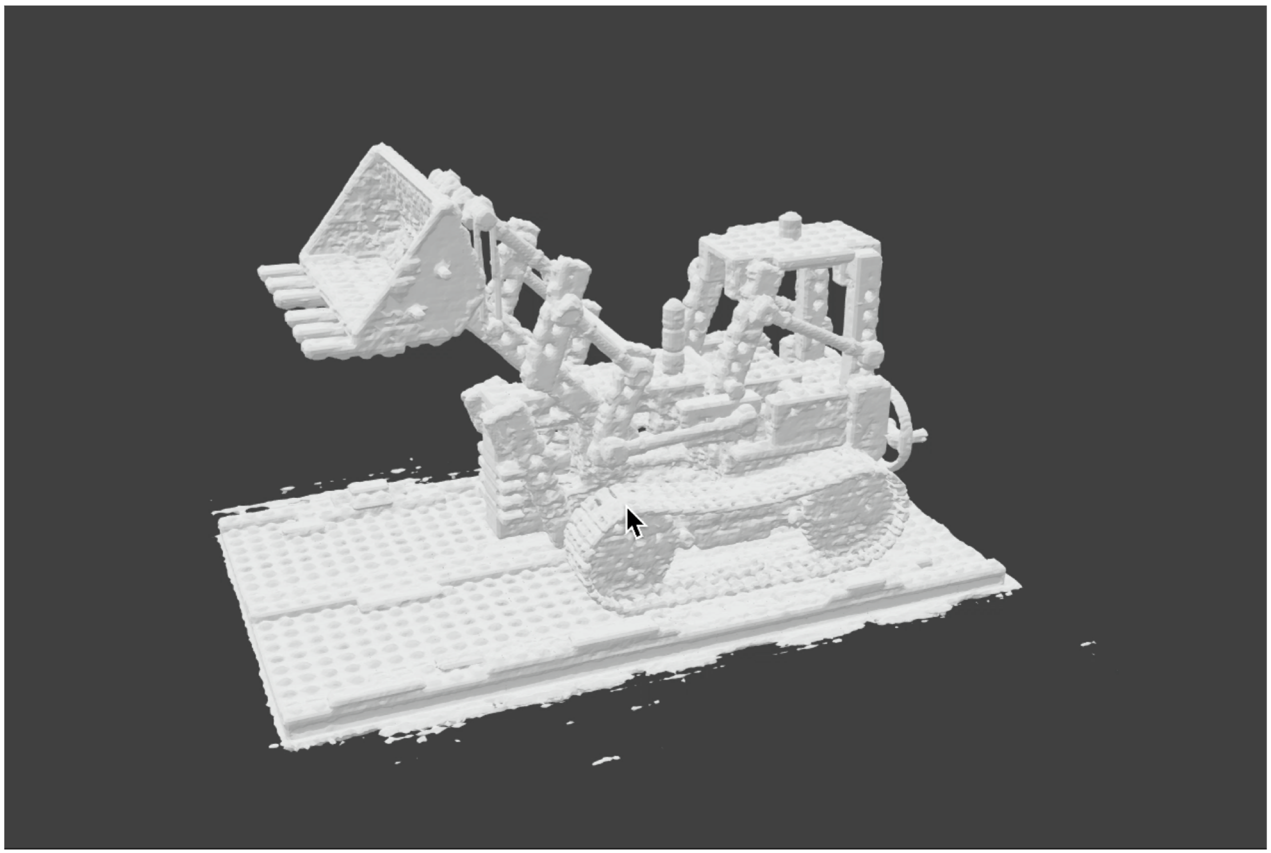
Viewpoint-dependent effects

Rendering expected depth

$$d(\mathbf{r}) \approx \sum_{i}^{N} T_i \alpha_i z_i$$

Because it models the entire plenoptic function you can insert objects with proper occlusion effects (in contrast to lightfields)

Extract surface on high density regions



NeRF limitations

- Expensive / slow to train and render
- Sensitive to sampling strategy
- Does not generalize between scenes
- Sensitive to pose accuracy
- Assumes static scene
- Assumes static lighting and camera focus
- Not a mesh

NeRF explosion

Awesome Neural Radiance Fields

A curated list of awesome neural radiance fields papers, inspired by awesome-computer-vision.

How to Pull Request?

If you are interested in adding papers, feel free to submit a pull request following the instruction here.

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- Neural Volume Rendering: NeRF And Beyond, Dellaert and Yen-Chen, Arxiv 2020 | blog | github

Papers

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- NeRF++: Analyzing and Improving Neural Radiance Fields, Zhang et al., Arxiv 2020 | github | bibtex
- DeRF: Decomposed Radiance Fields, Rebain et al. Arxiv 2020 | bibtex
- NeRD: Neural Reflectance Decomposition from Image Collections, Boss et al., Arxiv 2020 | github | bibtex
- NeRF--: Neural Radiance Fields Without Known Camera Parameters, Wang et al., Arxiv 2021 | github | bibtex

Faster Inference

- Neural Sparse Voxel Fields, Liu et al., NeurIPS 2020 | github | bibtex
- AutoInt: Automatic Integration for Fast Neural Volume Rendering, Lindell et al., Arxiv 2020 | bibtex

Unconstrained Images

- NeRF in the Wild: Neural Radiance Fields for Unconstrained Photo Collections, Martin-Brualla et al., Arxiv 2020 | bibtex

Deformable

- Deformable Neural Radiance Fields, Park et al., Arxiv 2020 | github | bibtex
- D-NeRF: Neural Radiance Fields for Dynamic Scenes, Pumarola et al., Arxiv 2020 | bibtex
- Dynamic Neural Radiance Fields for Monocular 4D Facial Avatar Reconstruction, Gafni et al., Arxiv 2020 | bibtex
- Non-Rigid Neural Radiance Fields: Reconstruction and Novel View Synthesis of a Deforming Scene from Monocular Video, Tretschk et al., Arxiv 2020 | github | bibtex

Video

- Neural Scene Flow Fields for Space-Time View Synthesis of Dynamic Scenes, Li et al., Arxiv 2020 | bibtex
- Space-time Neural Irradiance Fields for Free-Viewpoint Video, Xian et al., Arxiv 2020 | bibtex
- Neural Radiance Flow for 4D View Synthesis and Video Processing, Du et al., Arxiv 2020 | bibtex
- Neural Body: Implicit Neural Representations with Structured Latent Codes for Novel View Synthesis of Dynamic Humans, Peng et al., Arxiv 2020 | bibtex

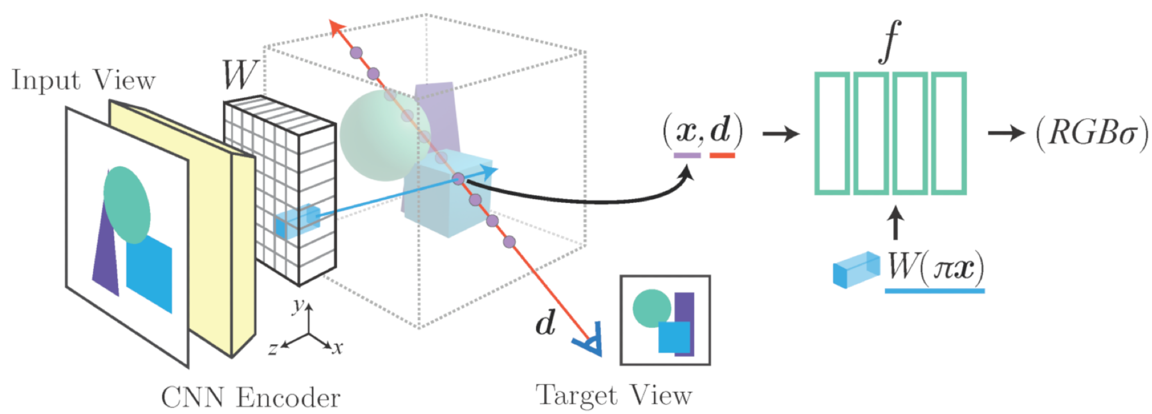
Generalization

- GRAF: Generative Radiance Fields for 3D-Aware Image Synthesis, Schwarz et al., NeurIPS 2020 | github | bibtex
- GRF: Learning a General Radiance Field for 3D Scene Representation and Rendering, Trevithick and

https://github.com/yenchenlin/awesome-NeRF

NeRF generalizations

- PixelNeRF [Yu et al. CVPR'21]
- IBRNet [Wang et al. CVPR'21]
- MVSNeRF [Yao et al. ICCV'21]
- NerfingMVS [Wei et al. ICCV'21]
- NeRFormer [Reizenstein et al. ICCV'21]
- GRF [Trevithick et al. ICCV'21]
- …



PixelNeRF [Yu et al. CVPR'21]

NeRF in the wild

R. Martin-Brualla et al. NeRF in the Wild. CVPR 2021

PixelNeRF

Three input views

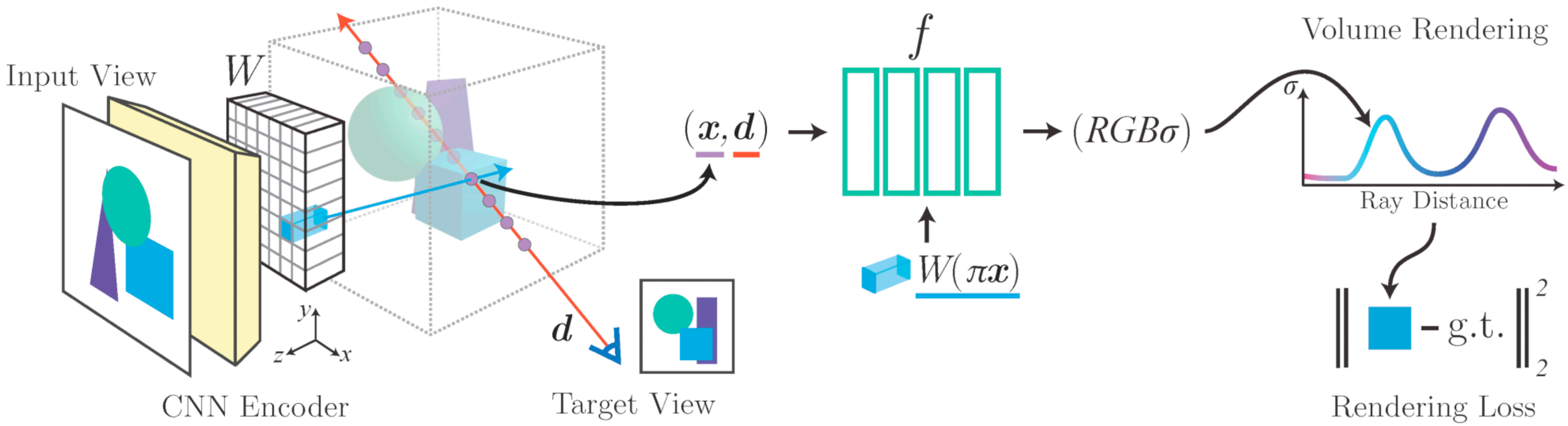
PixelNeRF 3-view NeRF

A. Yu et al. [PixelNeRF: Neural Radiance Fields from One or Few Images](). CVPR 2021

PixelNeRF

A. Yu et al. PixelNeRF: Neural Radiance Fields from One or Few Images. CVPR 2021

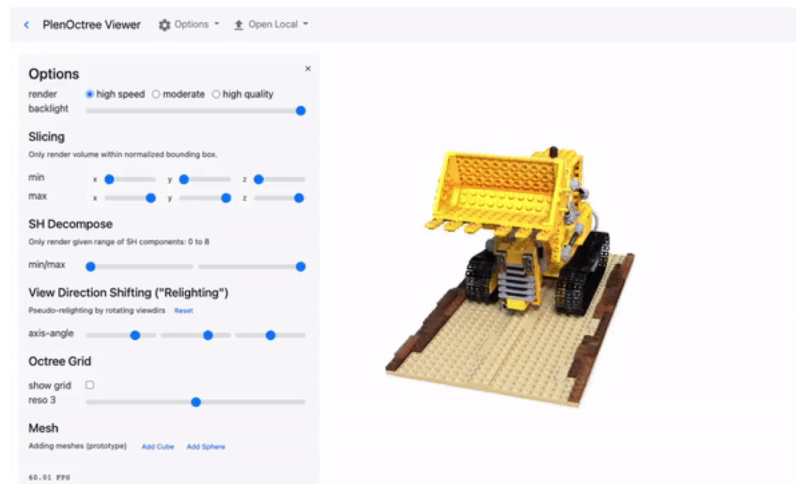
PixelNeRF



A. Yu et al. [PixelNeRF: Neural Radiance Fields from One or Few Images](). CVPR 2021

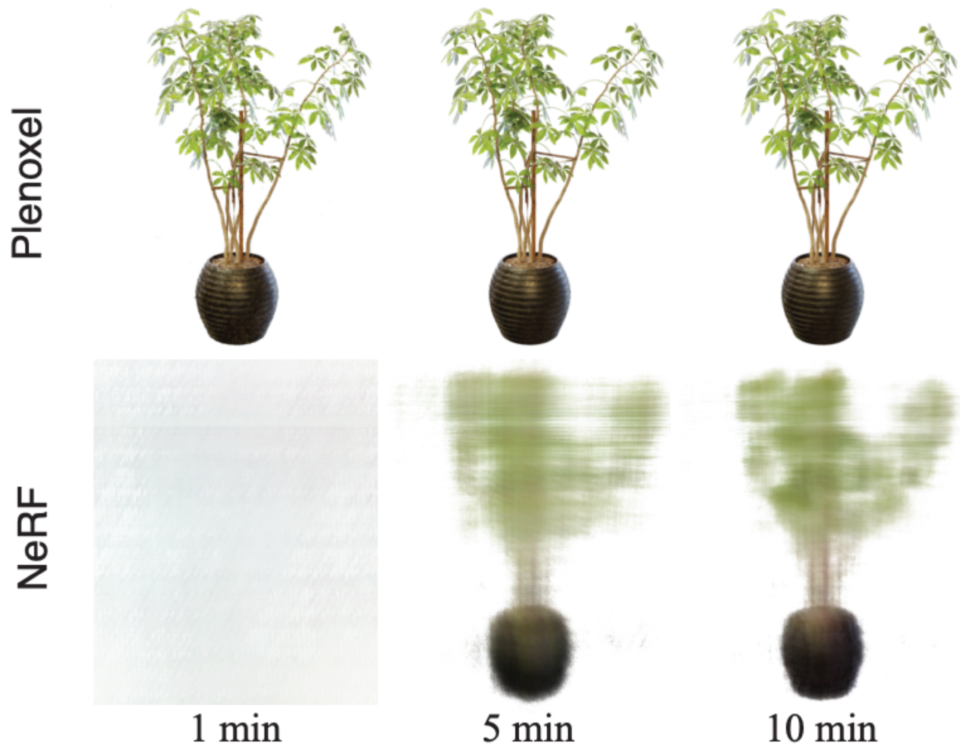
Fast Inference

- PlenOctrees [Yu et al. ICCV'21]
- SNeRG [Hedman et al. ICCV'21]
- FastNeRF [Garbin et al. ICCV'21]
- KiloNeRF [Reiser et al. ICCV'21]
- AutoInt [Lindell et al. CVPR'21]
- …



PlenOctrees [Yu et al. ICCV'21]

Plenoxels



S. Fridovich-Kiel et al. [Plenoxels: Radiance Fields without Neural Networks](). CVPR 2022

Plenoxels

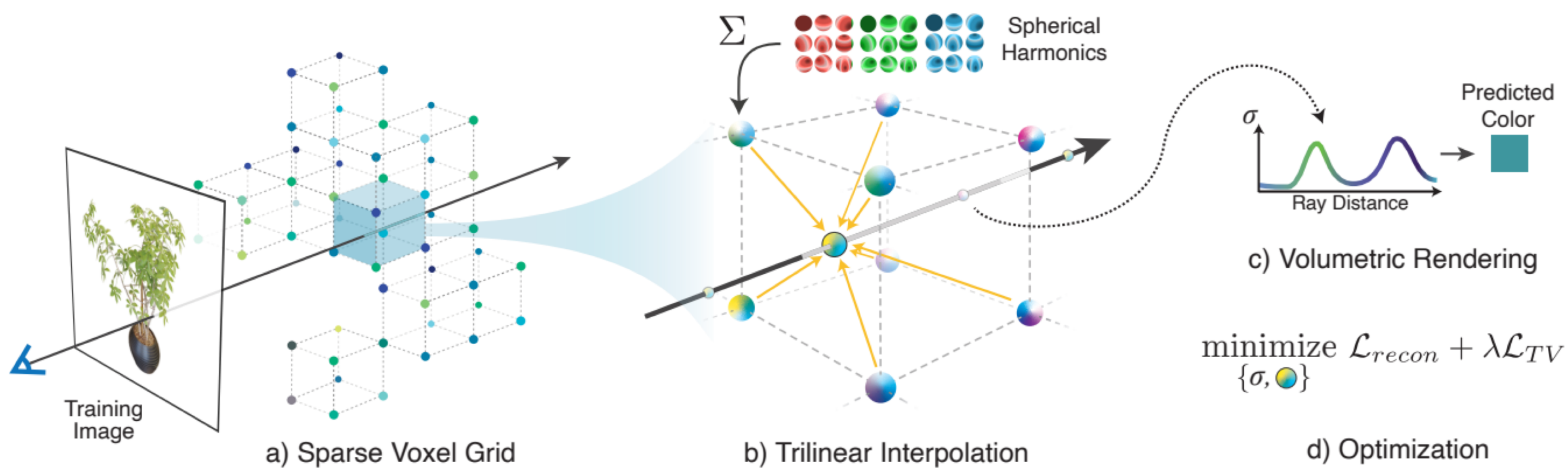


Figure 2. **Overview of our sparse Plenoxel model.** Given a set of images of an object or scene, we reconstruct a (a) sparse voxel ("Plenoxel") grid with density and spherical harmonic coefficients at each voxel. To render a ray, we (b) compute the color and opacity of each sample point via trilinear interpolation of the neighboring voxel coefficients. We integrate the color and opacity of these samples using (c) differentiable volume rendering, following the recent success of NeRF [26]. The voxel coefficients can then be (d) optimized using the standard MSE reconstruction loss relative to the training images, along with a total variation regularizer.

S. Fridovich-Kiel et al. [Plenoxels: Radiance Fields without Neural Networks](). CVPR 2022

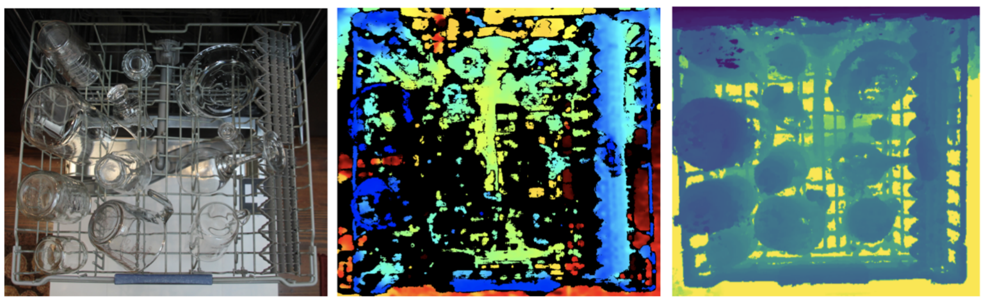
Pose Estimation

- GNeRF [Meng et al. ICCV ‘21]
- BARF [Lin et al. ICCV ‘21]
- NeRF– [Wang et al. arXiv ‘21]
- SC-NeRF [Jeong et al. ICCV ’21]
- iNeRF [Yen-Chen et al. IROS ‘21]

Input video. Predicted pose & image.

iNeRF [Yen-Chen et al. IROS ‘21]

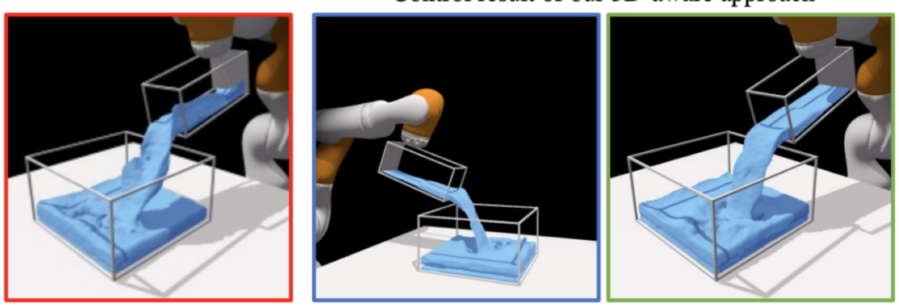
Robotics / Simulation



Real Image | RealSense Depth | Depth (NeRF-GTO)

NeRF-GTO: Using a Neural Radiance Field to Grasp Transparent Objects [Ichnowski et al. CoRL '21]

Control result of our 3D-aware approach



Goal image to achieve (camera view outside the training distribution) | Control results from the robot observation view | Control results from the goal image view

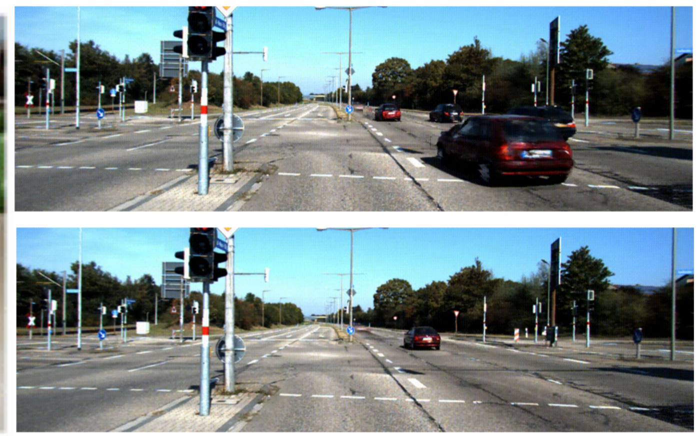
3D Neural Scene Representations for Visuomotor Control [Li et al. Corl '21]

Others: iMAP[Sucar ICCV'21]

Object Decomposition

ST-NeRF [Zhang et al. SISGRAPH ‘21]

Yang et al.



Neural Scene Graphs [Ost et al. CVPR ‘21]

Others: OSF [Guo et al.], uORF [Yu et al.]

Neural RGB-D surface reconstruction

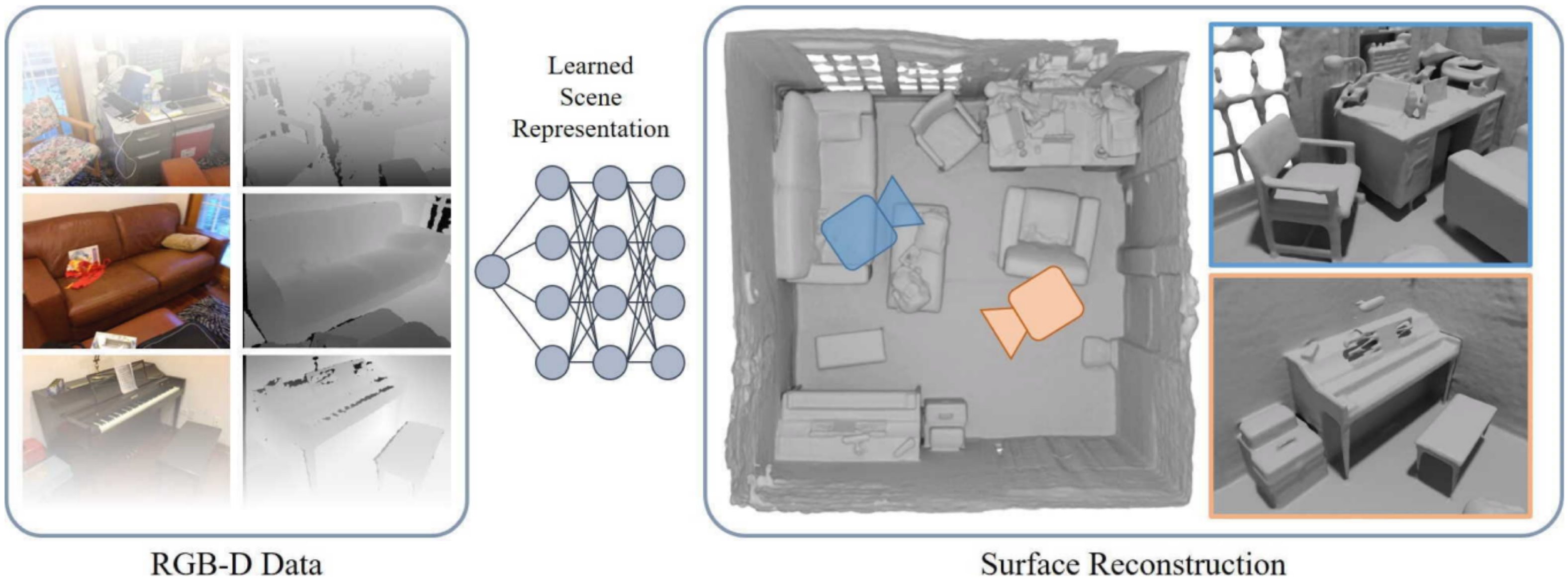
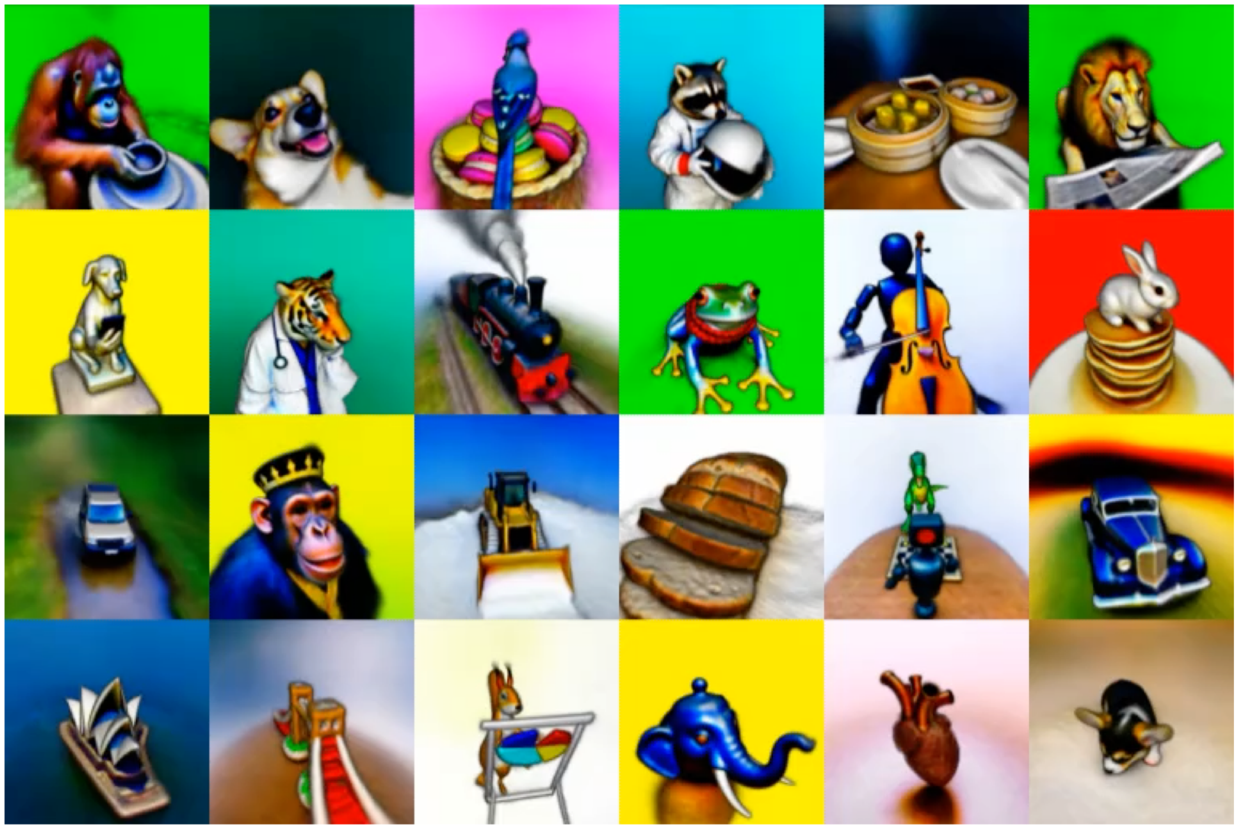


Figure 1. Our method obtains a high-quality 3D reconstruction from an RGB-D input sequence by training a multi-layer perceptron. The core idea is to reformulate the neural radiance field definition in NeRF [48], and replace it with a differentiable rendering formulation based on signed distance fields which is specifically tailored to geometry reconstruction.

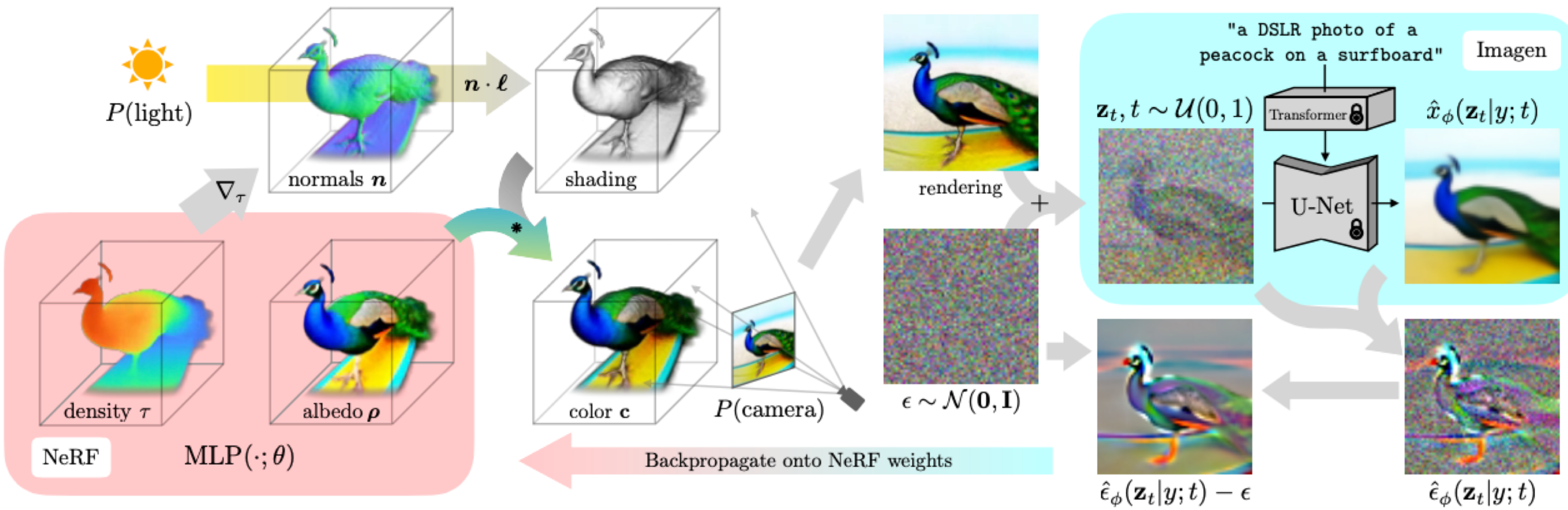
D. Azinovic et al. Neural RGB-D Surface Reconstruction. CVPR 2022

DreamFusion



B. Poole, A. Jain, J. Barron, B. Mildenhall. [DreamFusion: Text-to-3D using 2D Diffusion](). arXiv 2022

DreamFusion



B. Poole, A. Jain, J. Barron, B. Mildenhall. DreamFusion: Text-to-3D using 2D Diffusion. arXiv 2022