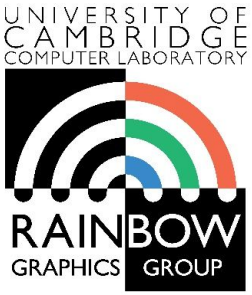

Advanced Graphics & Image Processing

Image-based rendering

Rafał Mantiuk
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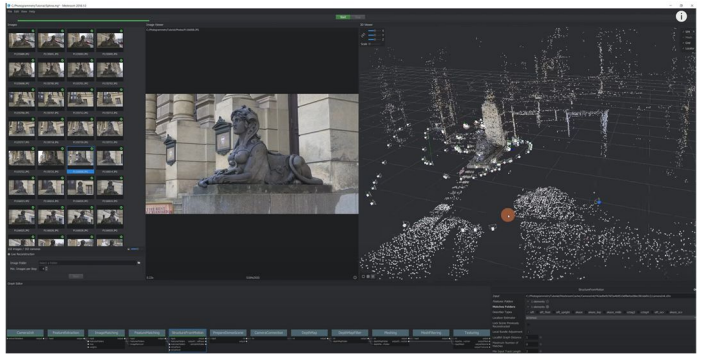
What is image-based rendering (IBR)?

- IBR ≈ use images for 3D rendering

3D mesh + textures + shading



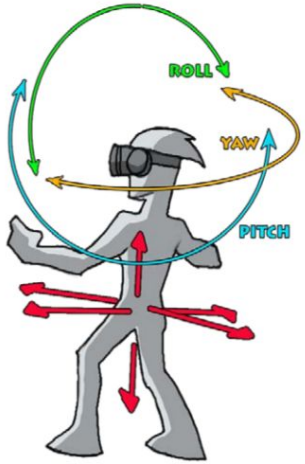
Photogrammetry

Neural Radiance Fields

- Our focus: methods that let us capture content with cameras

Motivation: why do we need image-based rendering?

- For inexpensive creation of high-quality 3D content
  - Minimize manual steps
  - Use cameras, which are good and abundant
- Why do we need 3D content?
  - AR/VR (+ novel display tech)
  - User-created content
  - 3D-printing
  - E-commerce



3D computer graphics

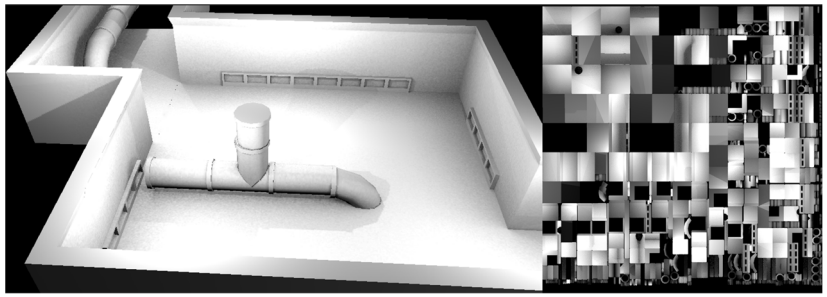
- We need:
  - Geometry + materials + textures
  - Lights
- Full control of illumination, realistic material appearance
- Graphics assets are expensive to create
- Rendering can be expensive
  - Shading tends to takes most of the computation

Cyberpunk 2077 (C) 2020 by CD Projekt RED

Baked / precomputed illumination

- We need:
  - Geometry + textures + (light maps)
- No need to scan and model materials
- Much faster rendering – simplified shading

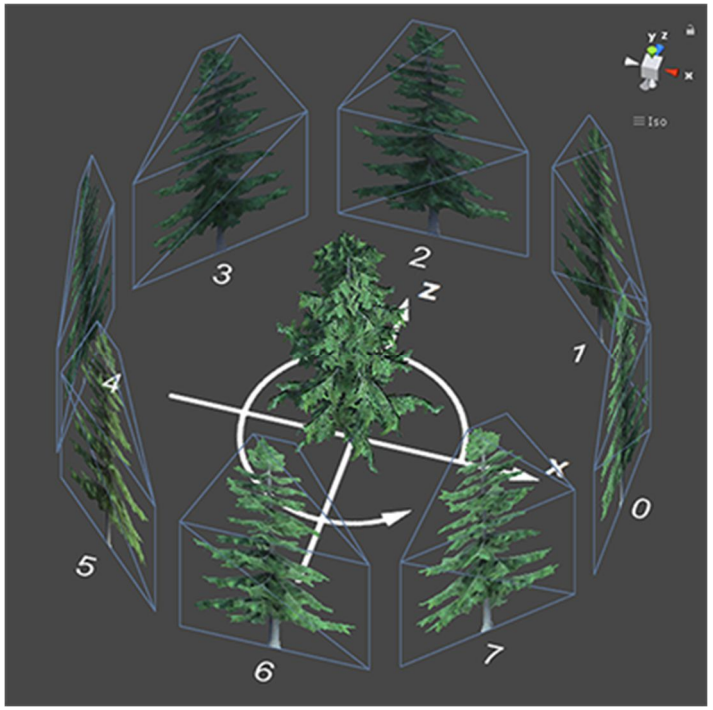
Google Earth



Precomputed light maps (from Wikipedia)

Billboards / Sprites

- We need:
  - Simplified geometry + textures (with alpha)
  - Lights
- Much faster to render than objects with 1000s of triangles
- Used for distant objects
  - or a small rendering budget
- Can be pre-computed from complex geometry



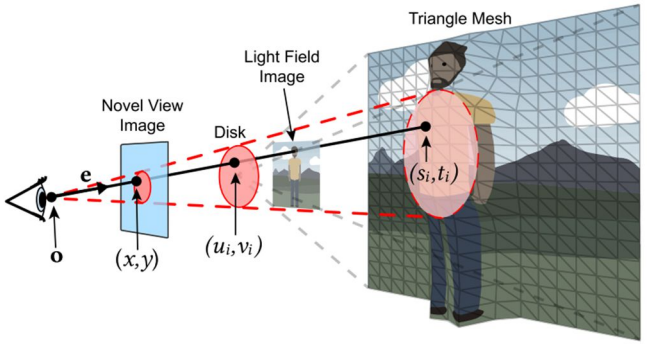
A tree rendered from a set of billboards
From:
https://docs.unity3d.com/ScriptReference/BillboardAsset.html

Light fields

- We need:
  - Images of the scene
    - Or a microlens image
- Does not need any geometry
  - But requires a large number of images for good quality
- Photographs are rep-projected on a (focal) plane
- No relighting

Light fields + depth

- We need:
  - Depth map
  - Images of the object/scene
- We can use camera-captured images
- View-dependent shading
- Depth-map can be computed using multi-view stereo techniques
- No relighting

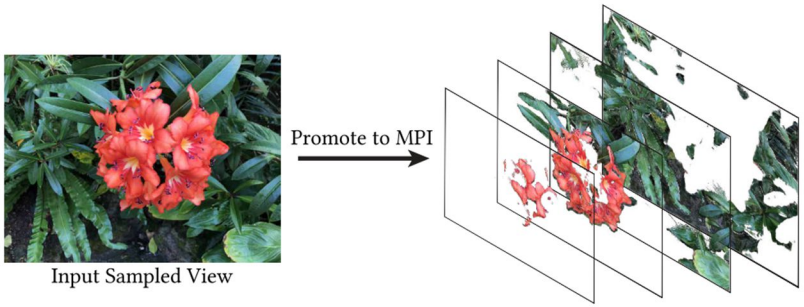


A depth map is approximated by triangle mesh and rasterized. From: Overbeck et al. TOG 2018, https://doi.org/10.1145/3272127.3275031.

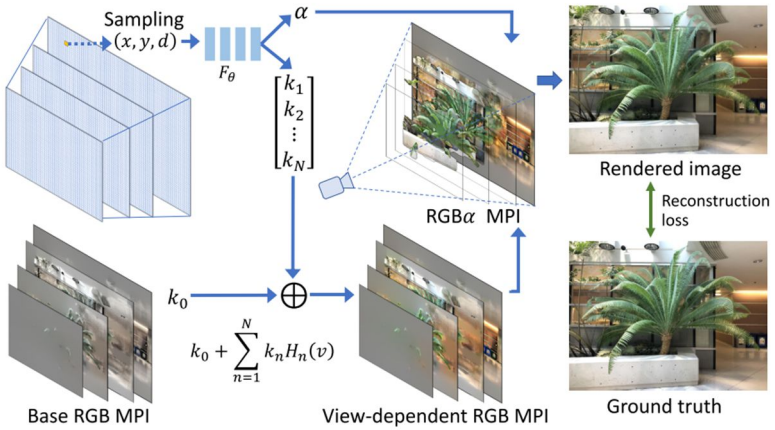
Demo: https://augmentedperception.github.io/welcome-to-lightfields/

Multi-plane images (MPI)

- We need:
  - Images of the scene + camera poses
- Each plane: RGB + alpha
  - Decomposition formulated as an optimization problem
  - Differential rendering
- Only front view



From [1]



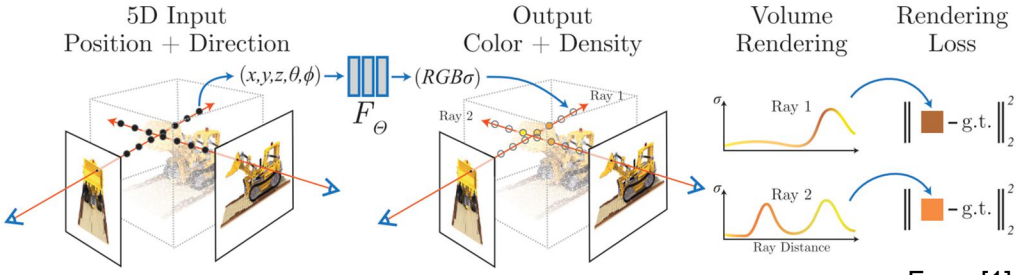
From [2]

[1] Mildenhall, et al. "Local Light Field Fusion." *ACM Transactions on Graphics* 38, no. 4 (July 12, 2019): 1–14. https://doi.org/10.1145/3306346.3322980

[2] Wizadwongsa et al. "NeX: Real-Time View Synthesis with Neural Basis Expansion." In *CVPR*, 8530–39. IEEE, 2021. https://doi.org/10.1109/CVPR46437.2021.00843 https://nex-mpi.github.io/

Neural Radiance Fields (NeRF)

- We need
  - Images of the scene + camera poses
- Similar to MPI but stored in a volumetric data structure
  - Implicit: multi-layer perceptron
  - Explicit: Voxel grid
- Volumetric differential rendering



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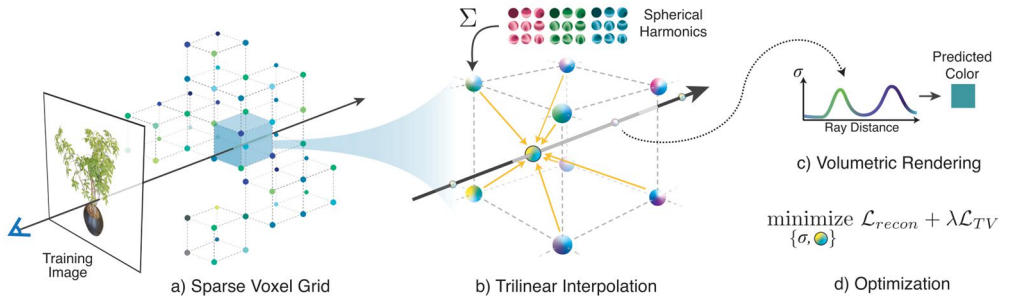
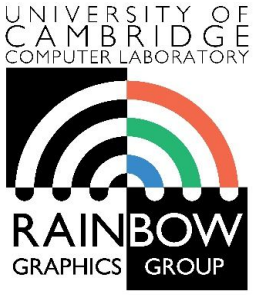


From [2]

[1] Mildenhall, et al. “NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis,” 405–21, 2020. https://doi.org/10.1007/978-3-030-58452-8_24.

[2] Yu et al. “Plenoxels: Radiance Fields without Neural Networks.” In *CVPR*, 5501–10, 2022. http://arxiv.org/abs/2112.05131.



Finite aperture imaging

imaging and lens

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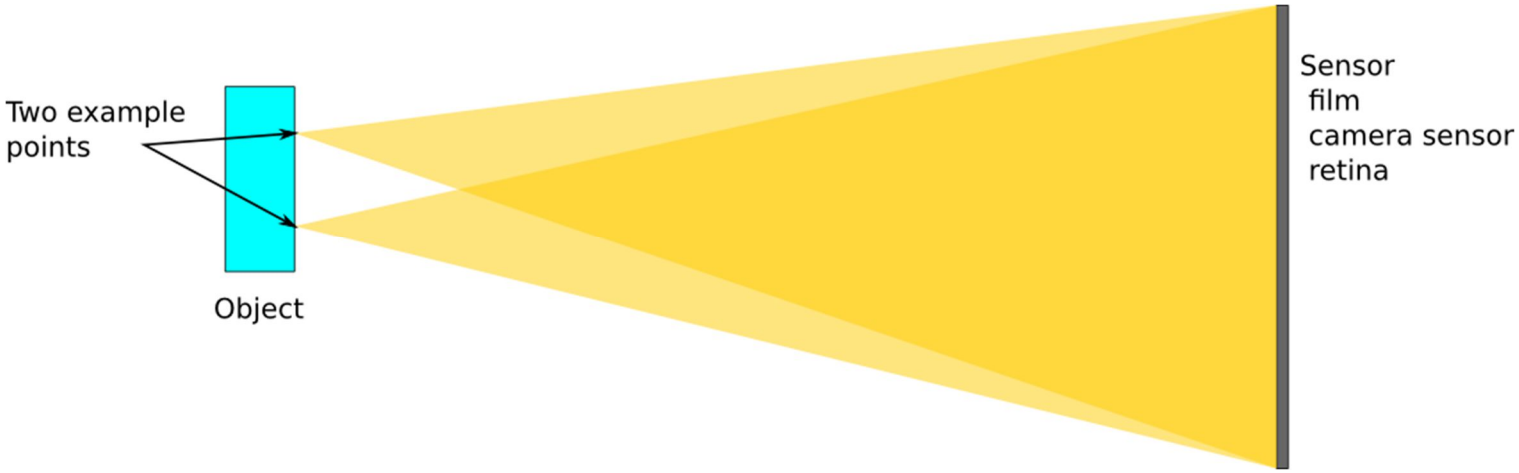
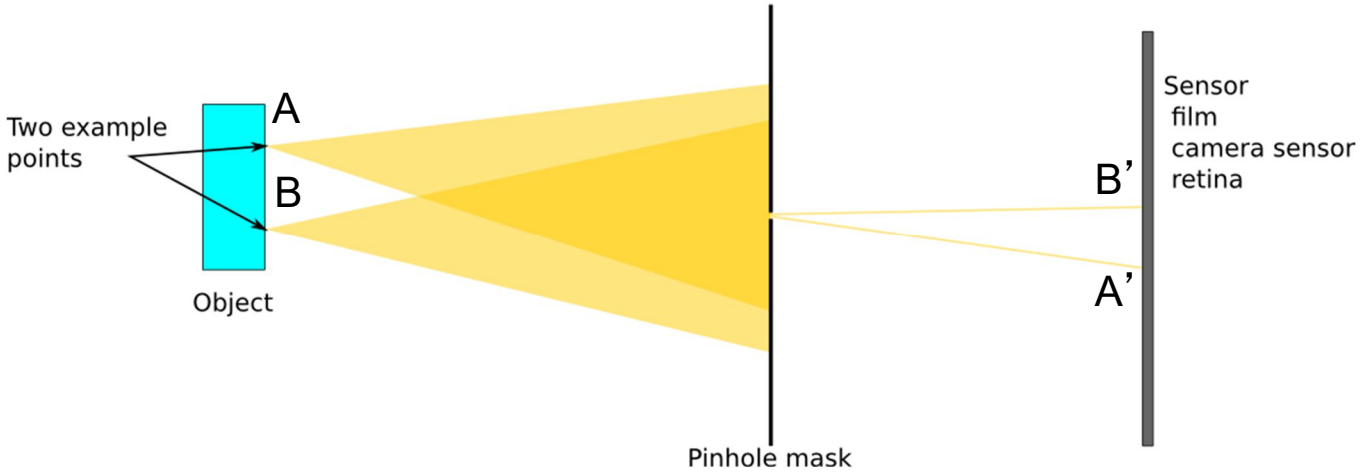
Imaging – without lens



Every point in the scene illuminates every point (pixel) on a sensor. Everything overlaps - no useful image.

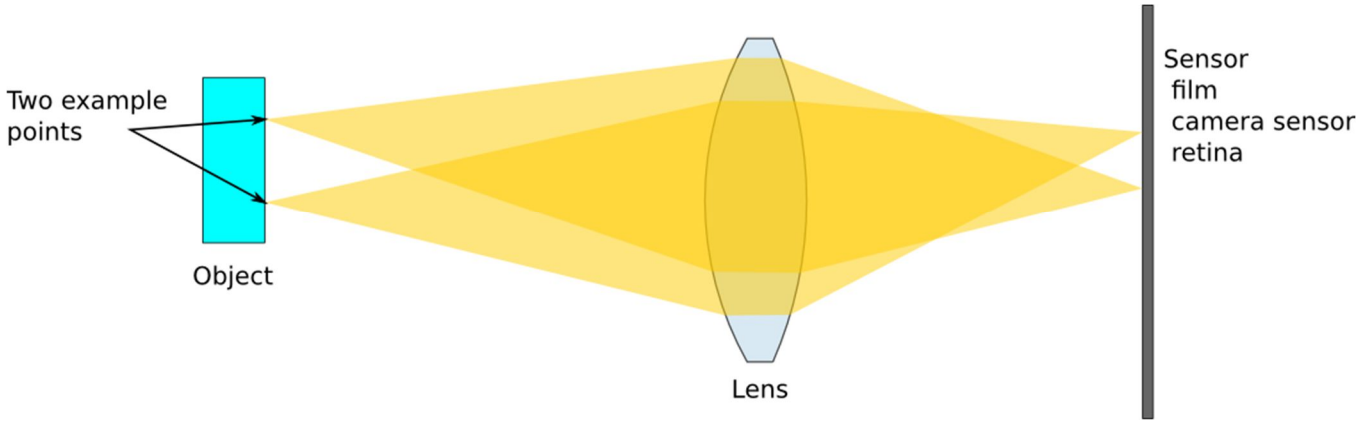
Imaging – pinhole camera



Pinhole masks all but only tiny beams of light. The light from different points is separated and the image is formed.

But very little light reaches the sensor.

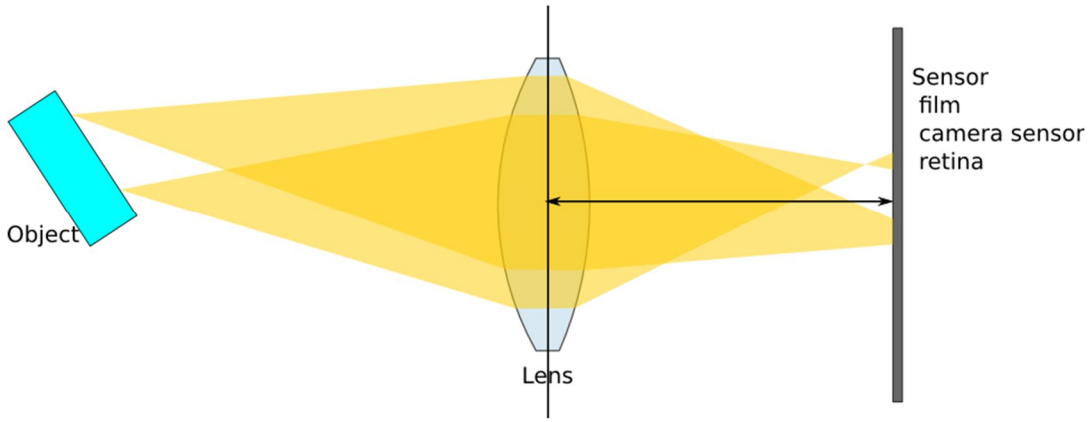
Imaging – lens



Lens can focus a beam of light on a sensor (focal plane).

Much more light-efficient than the pinhole.

Imaging – lens

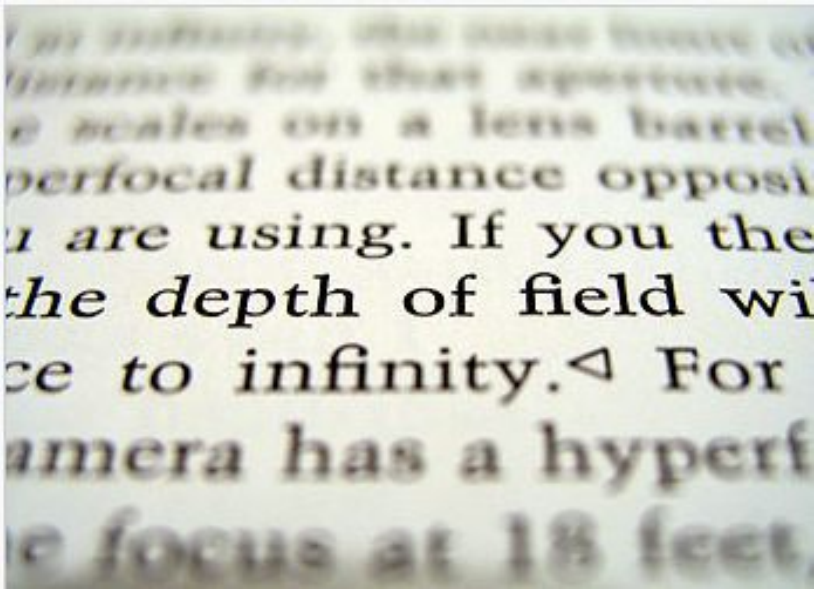


But it the light beams coming from different distances are not focused on the same plane.
These points will appear blurry in the resulting image.

Camera needs to move lens to focus an image on the sensor.

Depth of field

- Depth of field – range of depths that provides sufficient focus

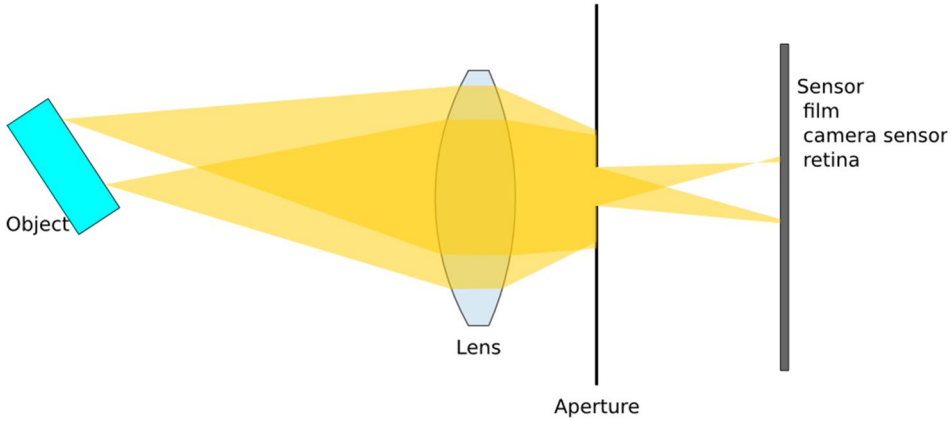


Defocus blur is often desirable

To separate the object of interest from background

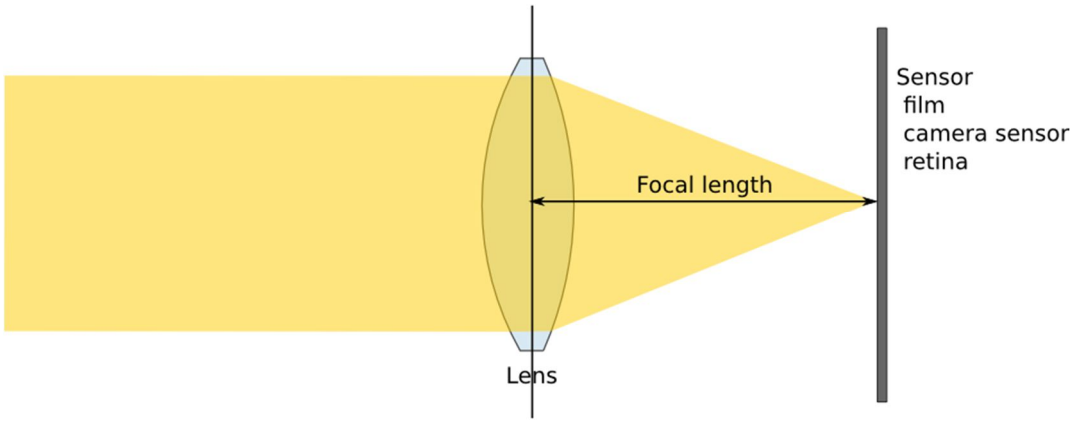
Defocus blur is a strong depth cue

Imaging – aperture



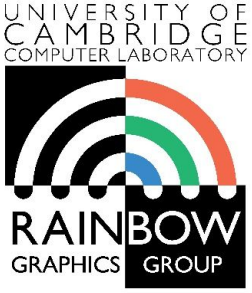
Aperture (introduced behind the lens) reduces the amount of light reaching sensor, but it also reduces blurriness from defocus (increases depth-of-field).

Imaging – lens



Focal length – length between the sensor and the lens that is needed to focus light coming from an infinite distance.

Larger focal length of a lens – more or less magnification?



Light fields

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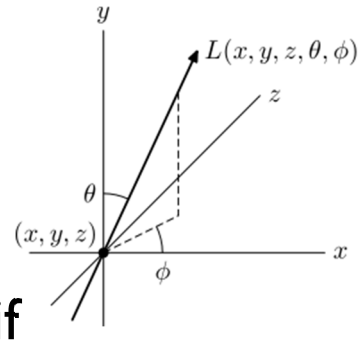
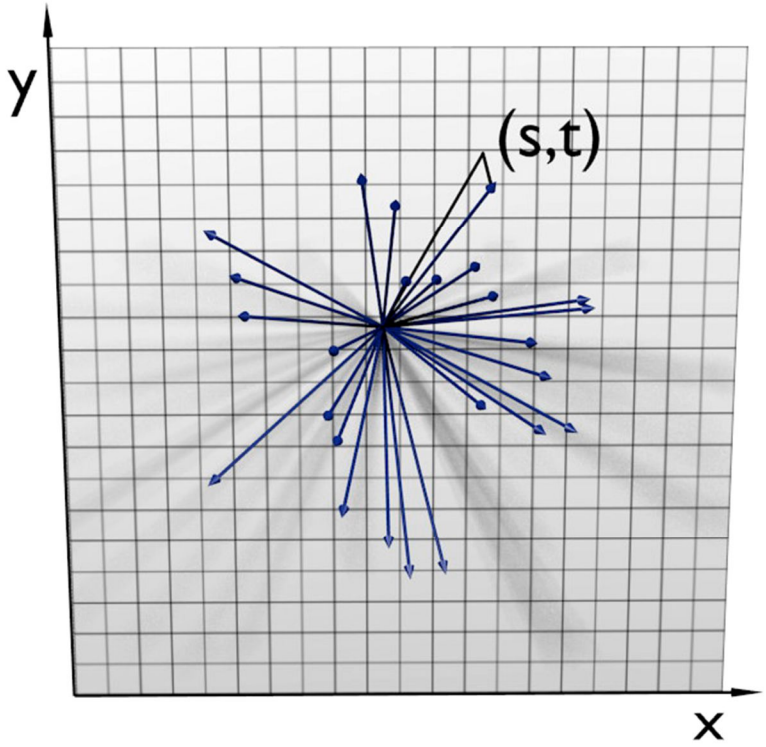
From a plenoptic function to a light field

- Plenoptic function – describes all possible rays in a 3D space
  - Function of position (x, y, z) and ray direction (θ, ϕ)
  - But also wavelength λ and time t
  - Between 5 and 7 dimensions

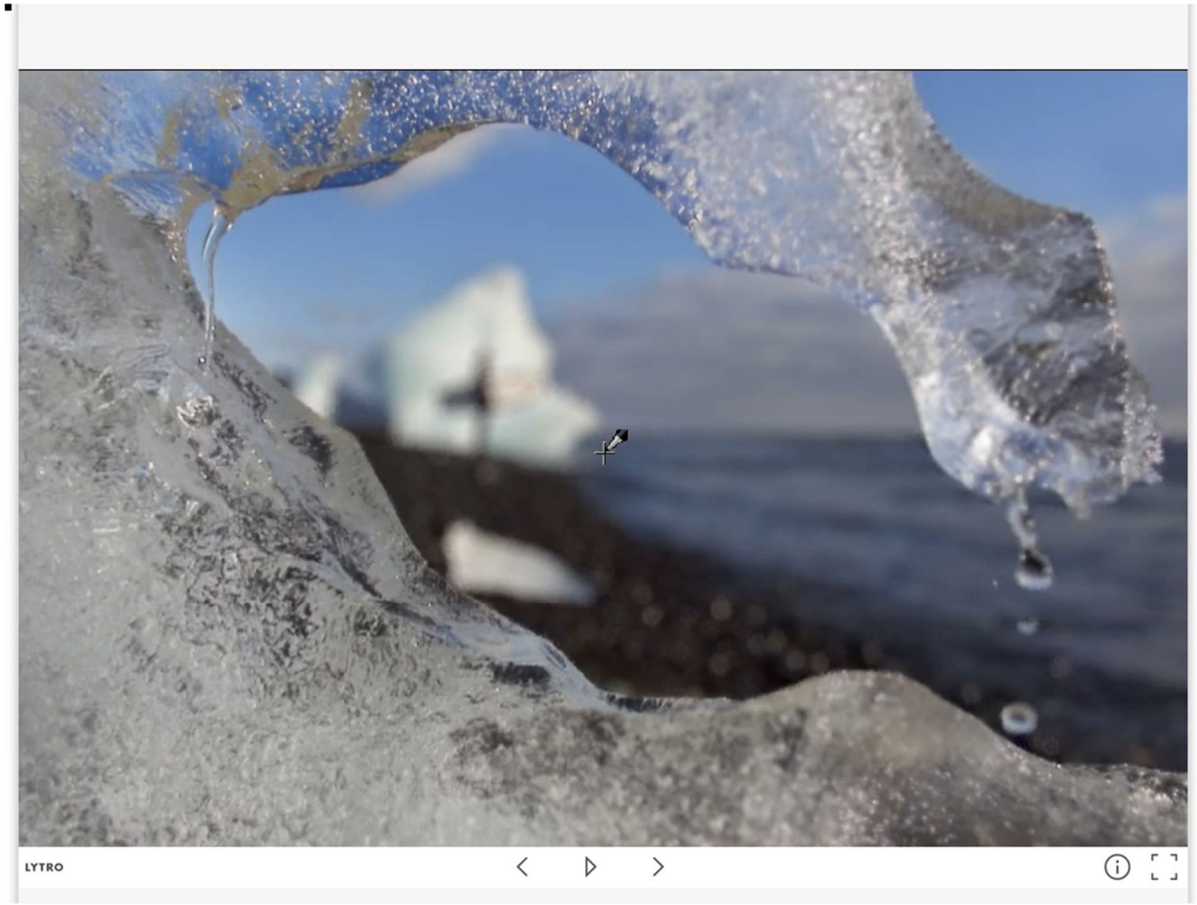


- But the number of dimensions can be reduced if
  - The camera stays outside the convex hull of the object
  - The light travels in uniform medium
  - Then, radiance L remains the same along the ray (until the ray hits an object)
  - This way we obtain a **4D light field**

Planar 4D light field



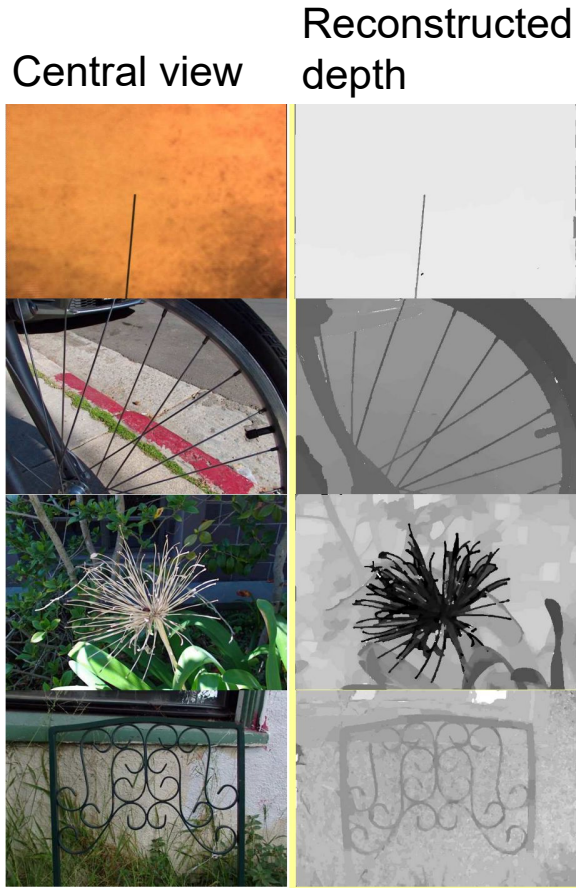
Refocusing and view point adjustment



Screen capture from http://www.lytro.com/

Depth estimation from light field

- Passive sensing of depth
- Light field captures multiple depth cues
  - Correspondance (disparity) between the views
  - Defocus
  - Occlusions



From: ***Ting-Chun Wang, Alexei A. Efros, Ravi Ramamoorthi***; The IEEE International Conference on Computer Vision (ICCV), 2015, pp. 3487-3495

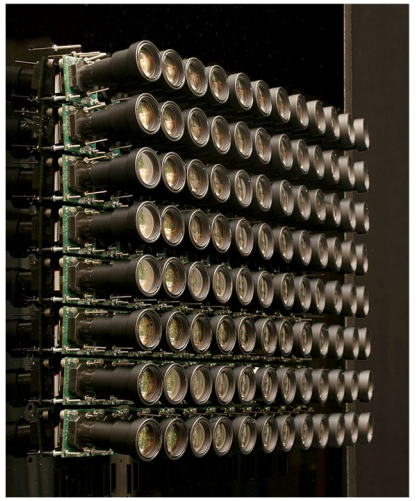
Two methods to capture light fields

Micro-lens array

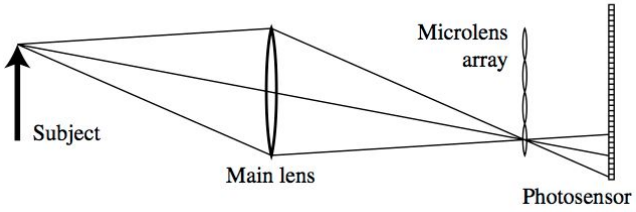
- Small baseline
- Good for digital refocusing
- Limited resolution

Camera array

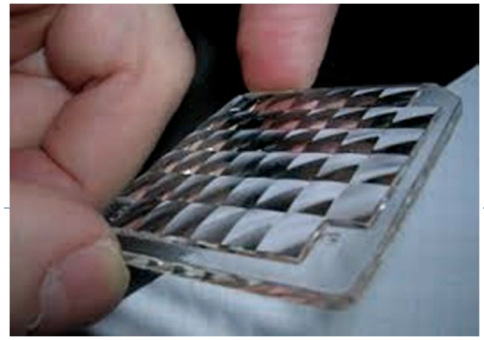
- Large baseline
- High resolution
- Rendering often requires approximate depth



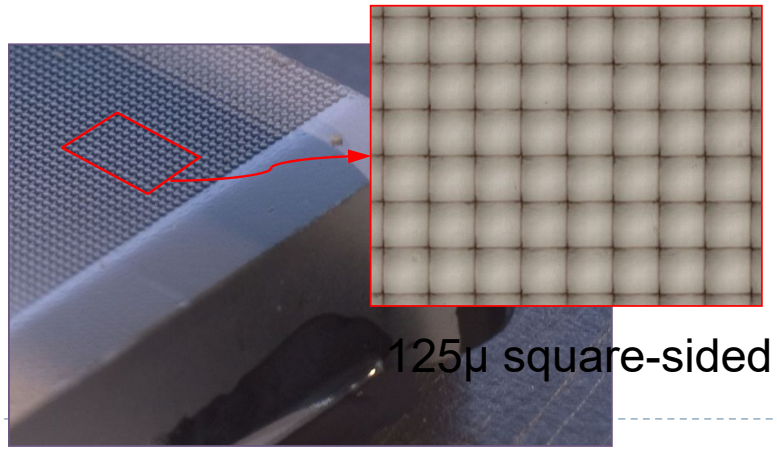
Light field image – with microlens array



Digital Refocusing using Light Field Camera



Lenslet array



125μ square-sided microlenses

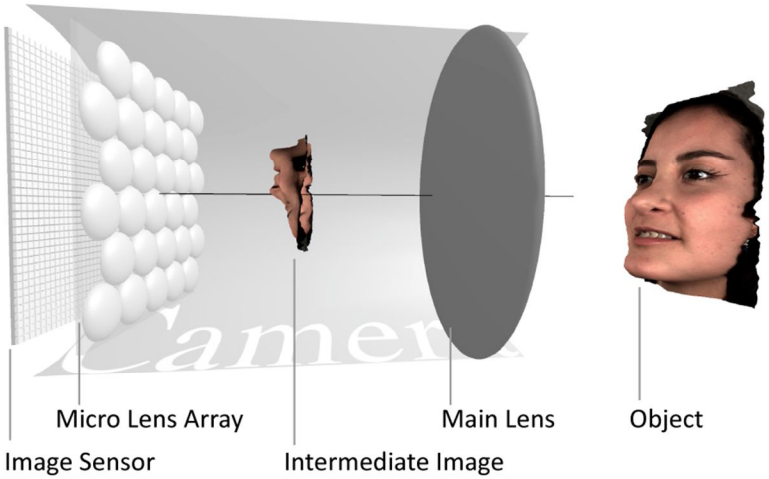
[Ng et al 2005]

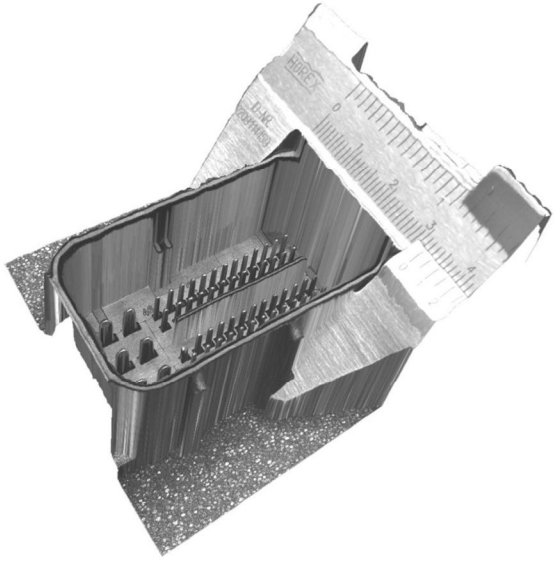
Lytro-cameras

- First commercial light-field cameras
- Lytro illum camera
  - 40 Mega-rays
  - 2D resolution: 2450 x 1634 (4 MPixels)

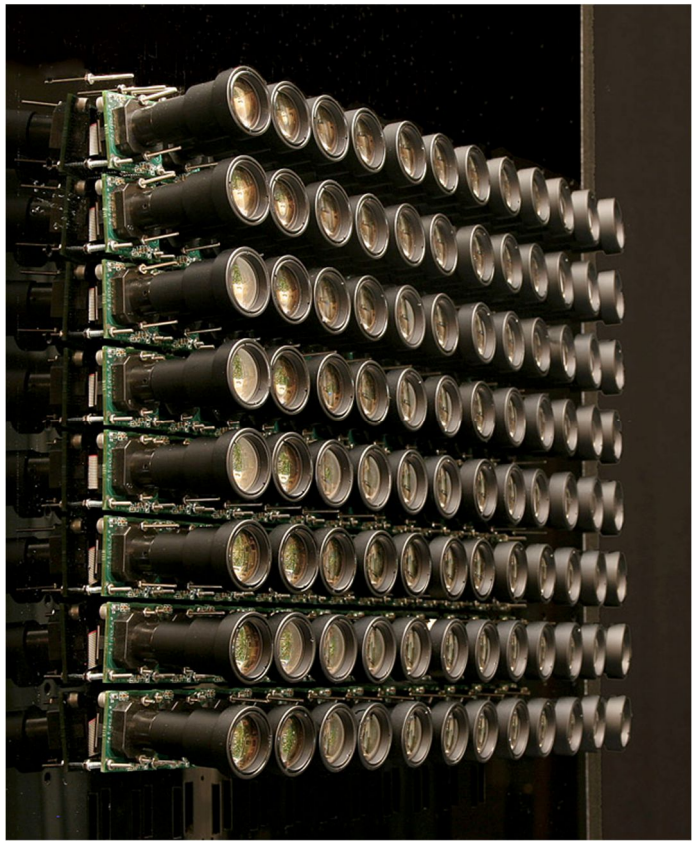
Raytrix camera

- Similar technology to Lytro
- But profiled for computer vision applications



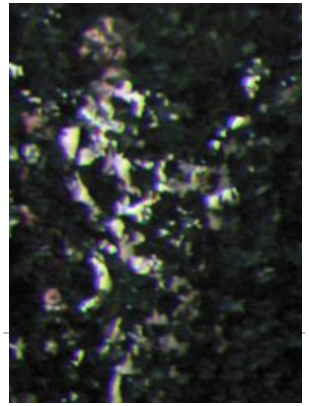


Stanford camera array



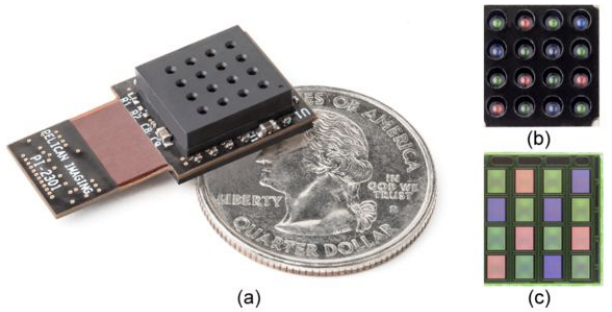
96 cameras

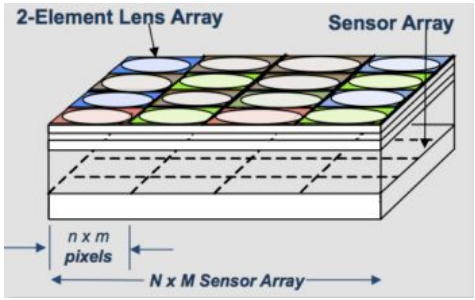
Application: Reconstruction of occluded surfaces

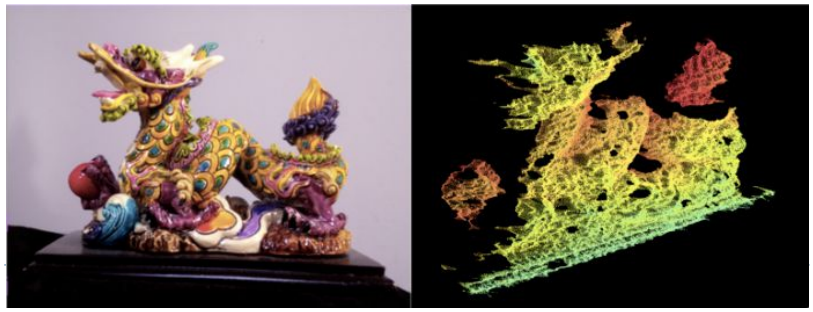


PiCam camera array module

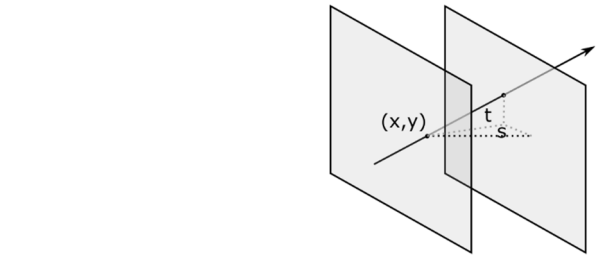
- Array of 4 x 4 cameras on a single chip
- Each camera has its own lens and senses only one spectral colour band
  - Optics can be optimized for that band
- The algorithm needs to reconstruct depth

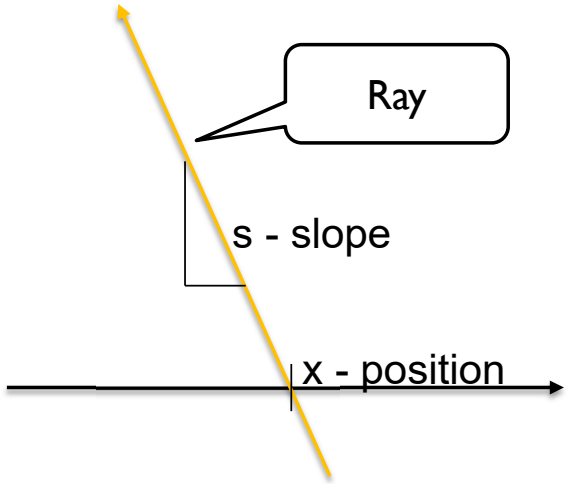




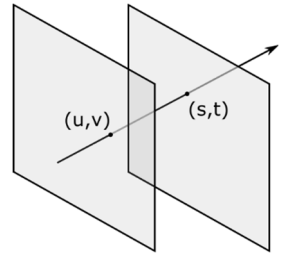


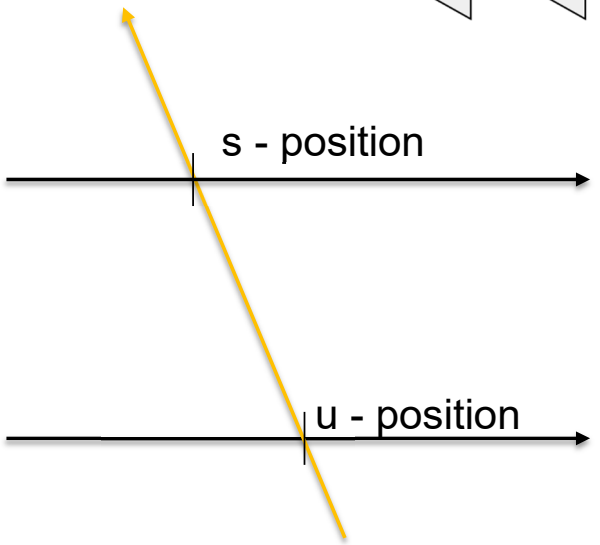
Light fields: two parametrisations (shown in 2D)





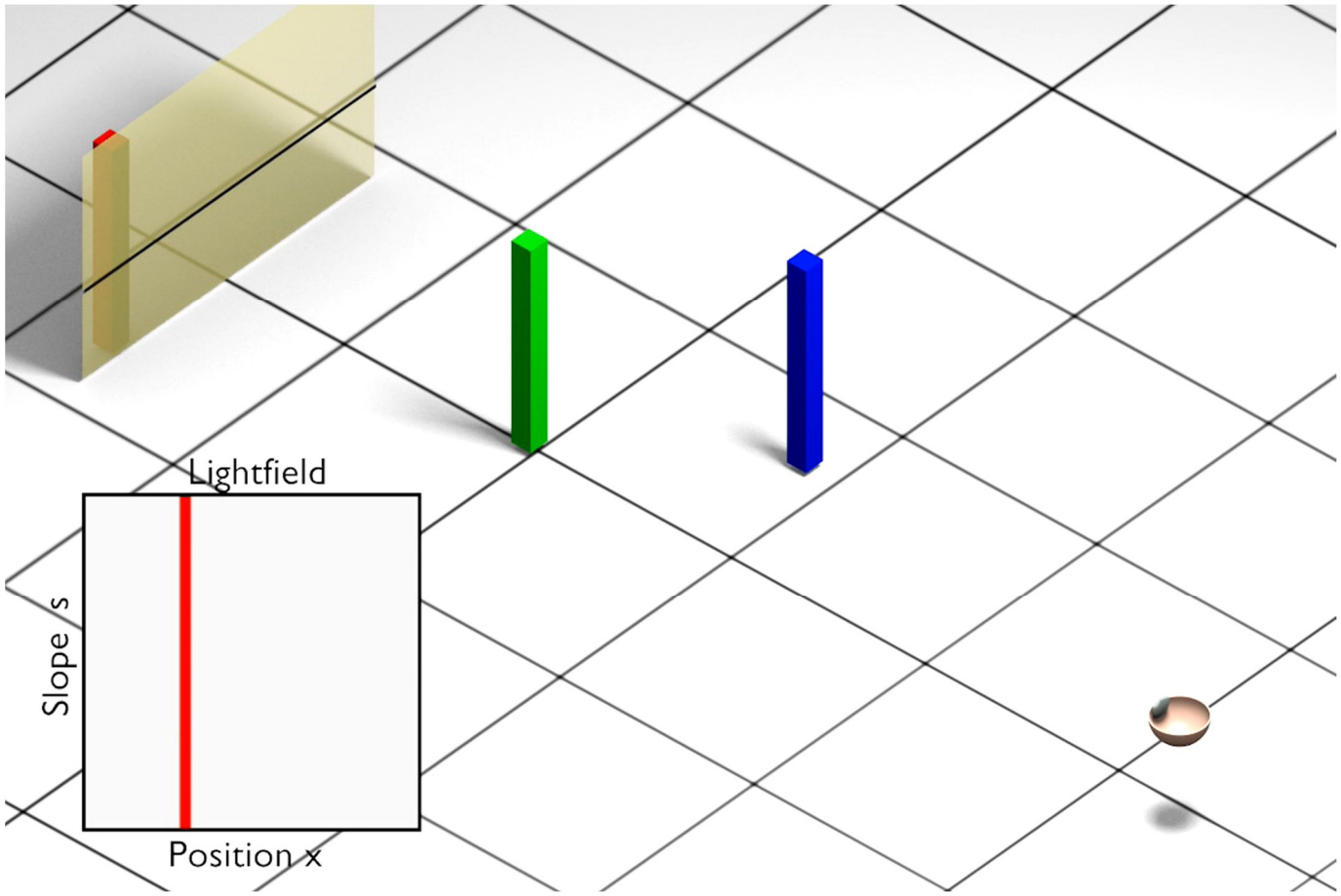
Position and slope
(slope - tangent of the angle)



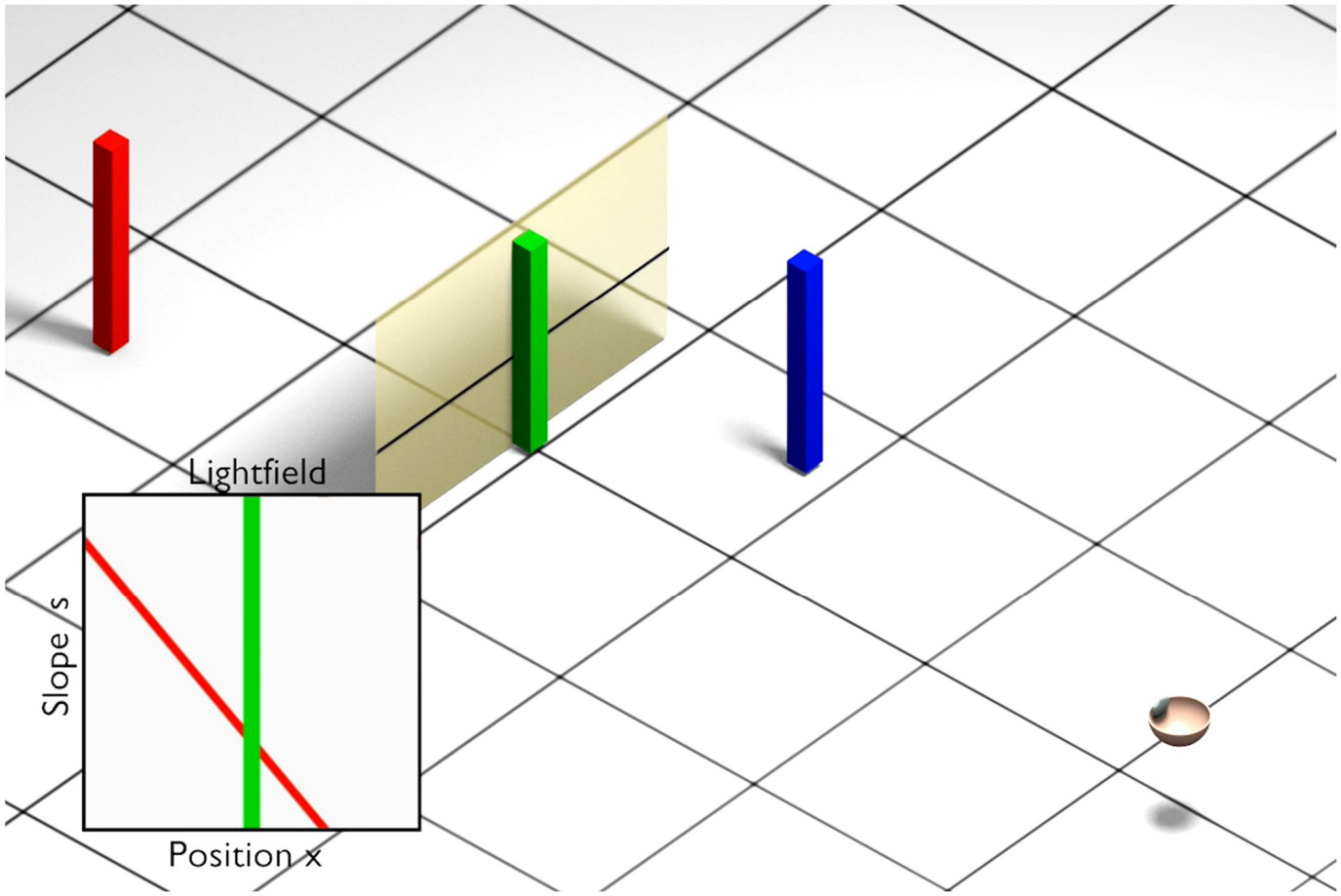


Two planes

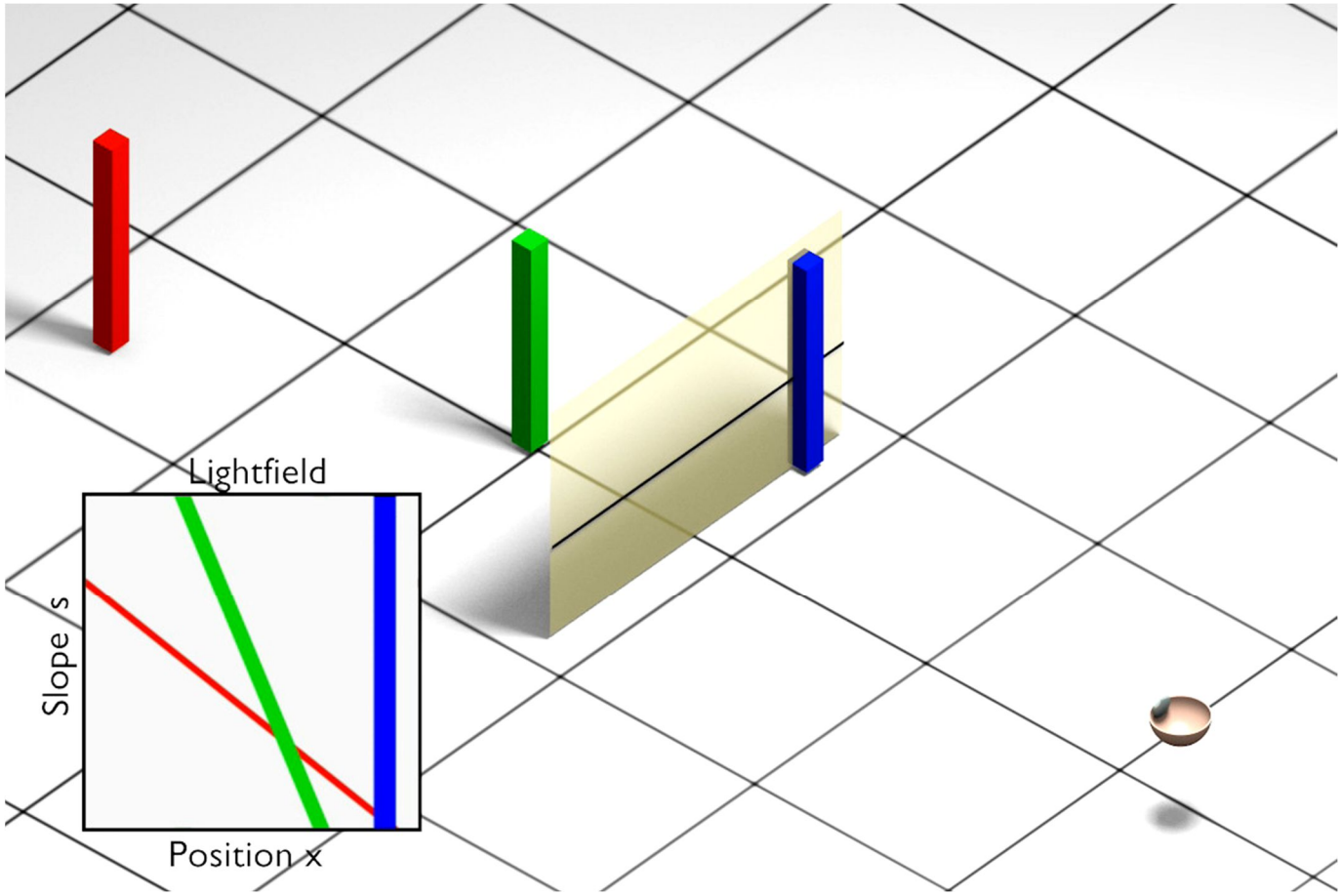
Lightfield - example



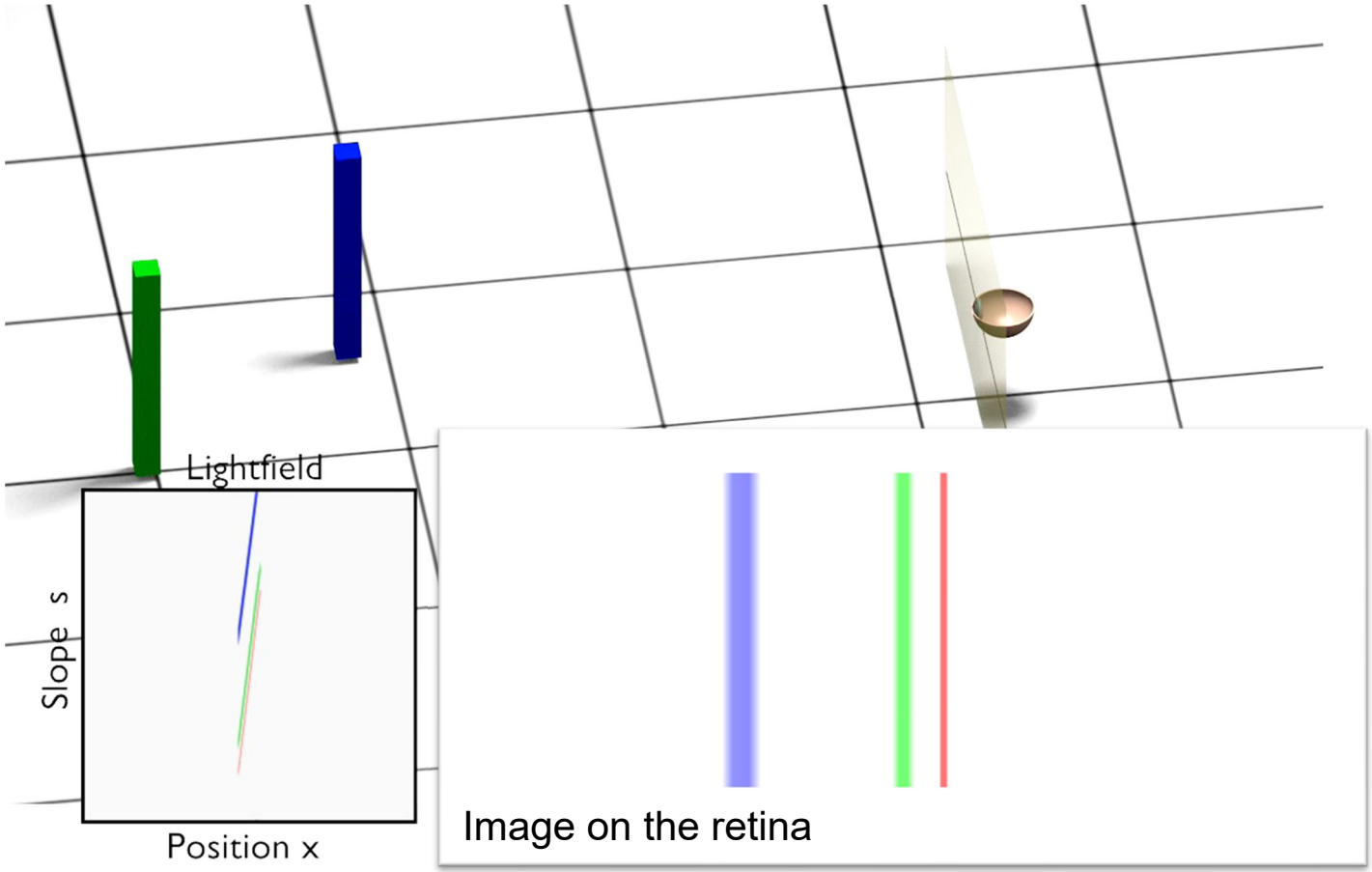
Lightfield - example

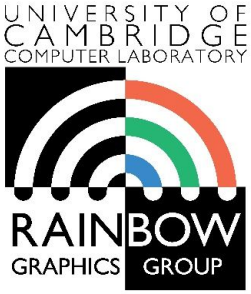


Lightfield - example



Lightfield - example

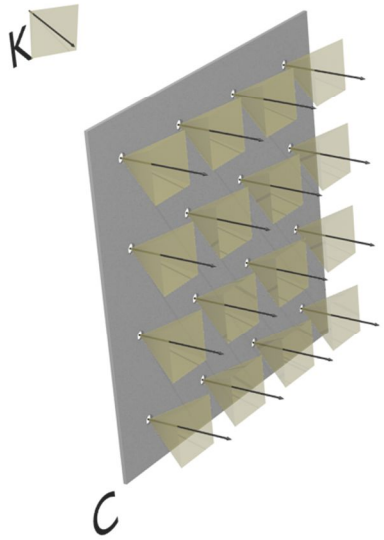




Light field rendering

Rafał Mantiuk
Computer Laboratory, University of Cambridge

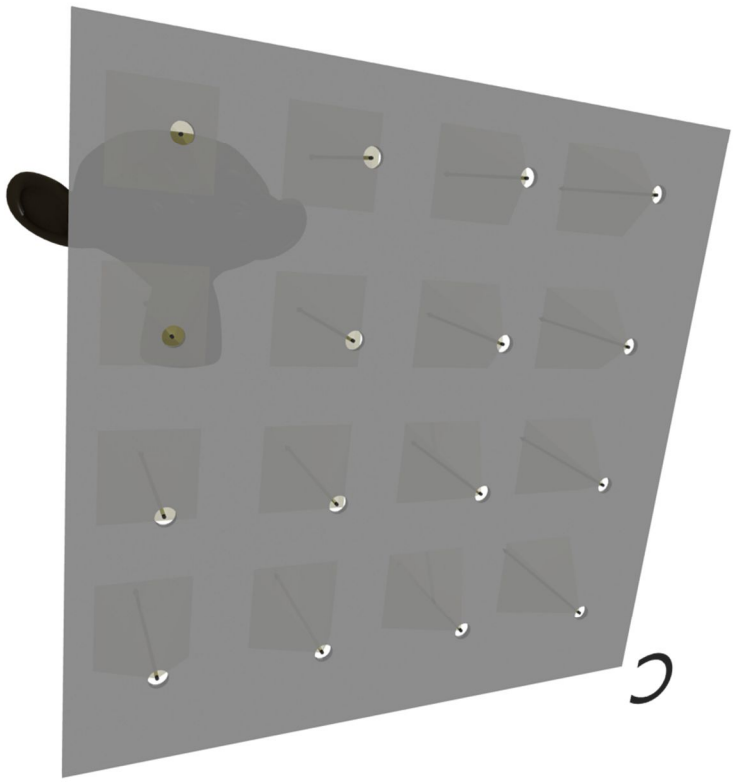
Light field rendering (1/3)



We want to render a scene (Blender monkey) as seen by camera K. We have a light field captured by a camera array. Each camera in the array has its aperture on plane C.

Light field rendering (2/3)

From the viewpoint of camera K

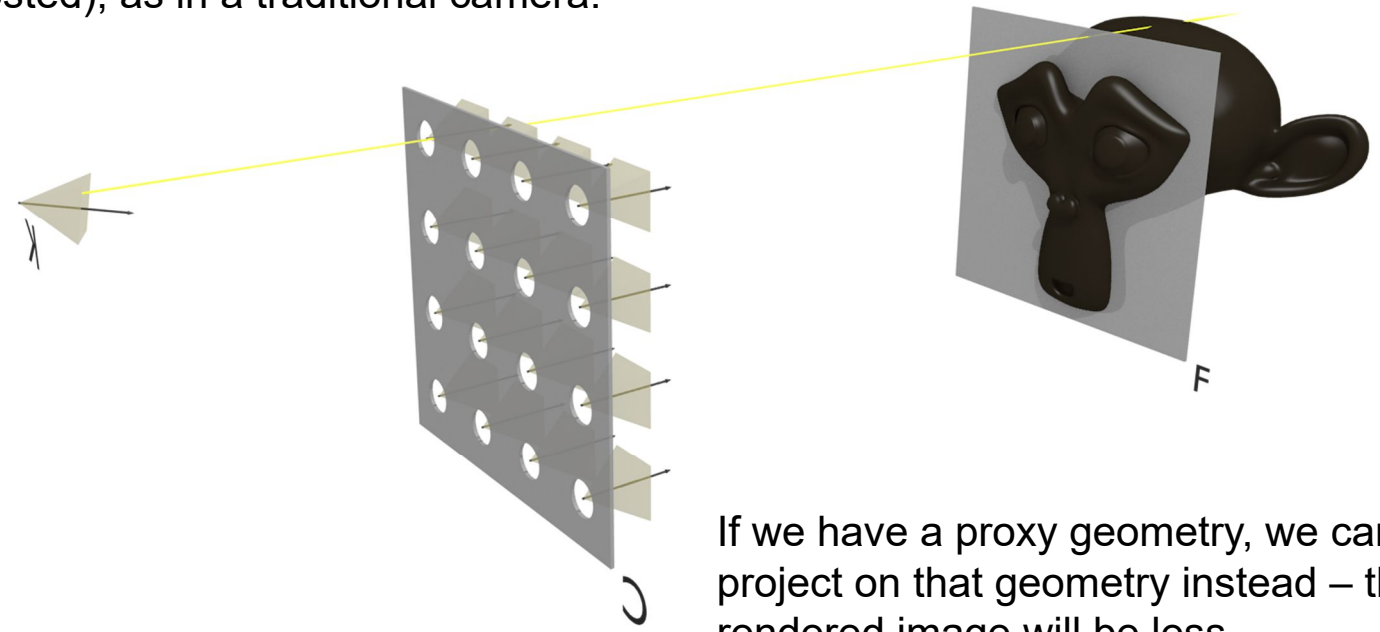


Each camera in the array provides accurate light measurements only for the rays originating from its pinhole aperture.

The missing rays can be either interpolated (reconstructed) or ignored.

Light field rendering (3/3)

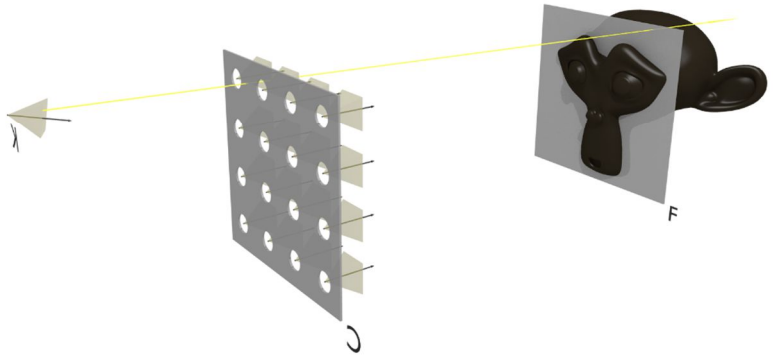
The rays from the camera need to be projected on the focal plane F. The objects on the focal plane will be sharp, and the objects in front or behind that plane will be blurry (ghosted), as in a traditional camera.



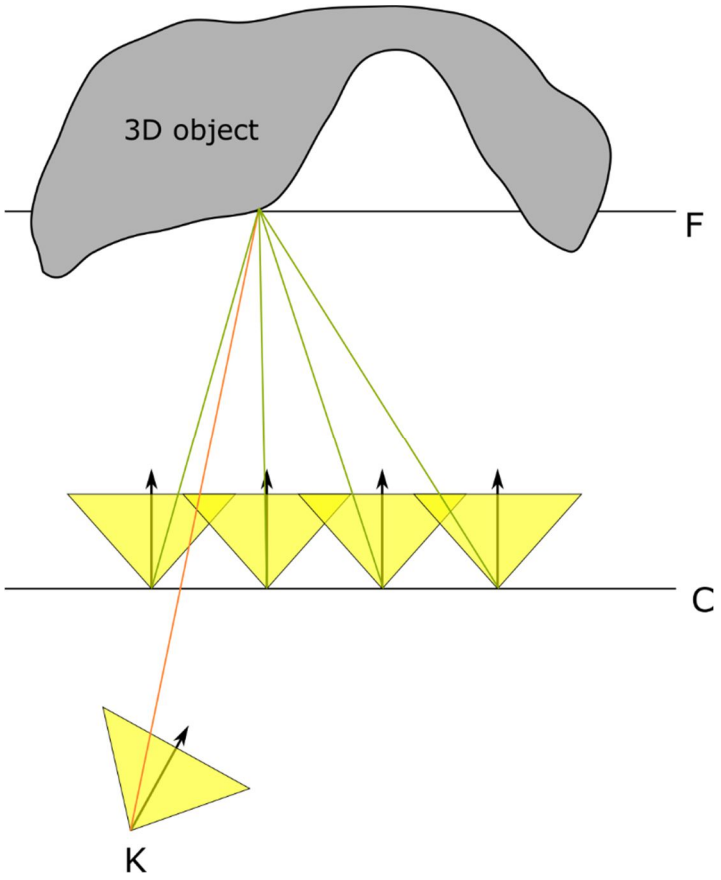
If we have a proxy geometry, we can project on that geometry instead – the rendered image will be less ghosted/blurry

Intuition behind light field rendering

- For large virtual aperture (use all cameras in the array)
  - Each camera in the array captures the scene
  - Then, each camera projects its image on the focal plane F
  - The virual camera K captures the projection
- For small virtual aperture (pinhole)
  - For each ray from the virtual camera
    - interpolate rays from 4 nearest camera images
  - Or use the nearest-neighbour ray

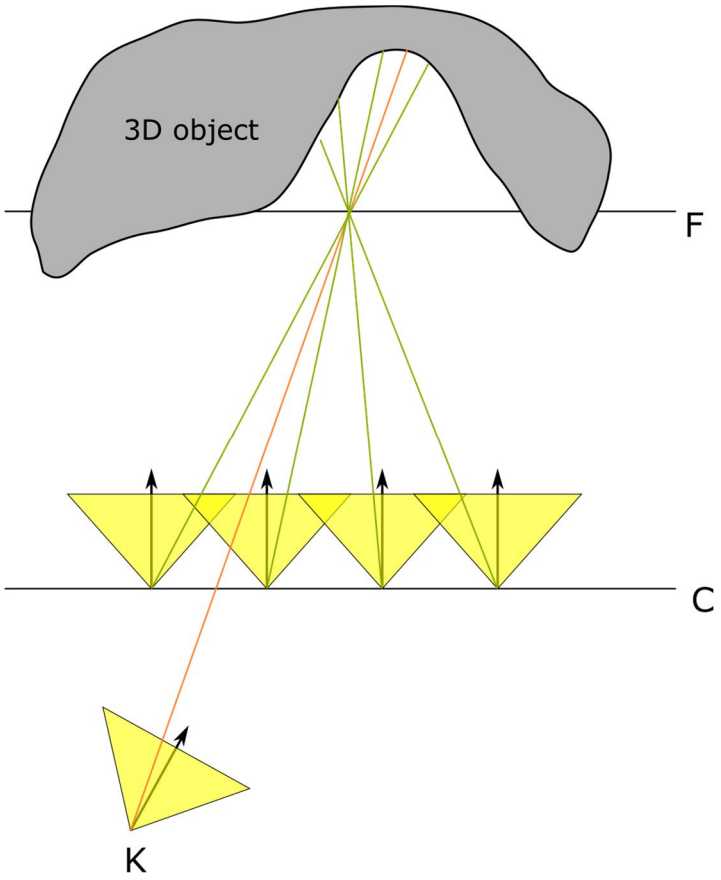


LF rendering – focal plane



- For a point on the focal plane, all cameras capture the same point on the 3D object
- They also capture approximately the same colour (for diffuse objects)
- Averaged colour will be the colour of the point on the surface

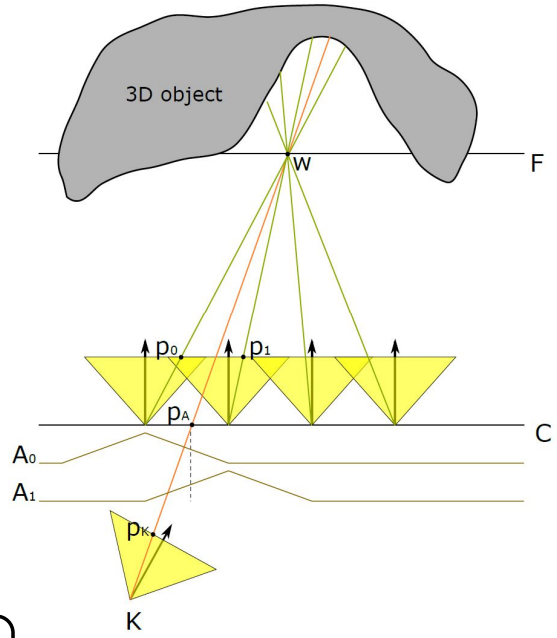
LF rendering – focal plane



- If the 3D object does not lie on the focal plane, all camaras capture different points on the object
- Averaging colour values will produce a „ghosted" image
- If we had unlimited number of cameras, this would produce a depth-of-field effect

Finding homographic transformation 1/3

- For the pixel coordinates $\boldsymbol{p}_k$ of the virtual camera K, we want to find the corresponding coordinates $\boldsymbol{p}_i$ in the camera array image
- Given the world 3D coordinates of a point $\boldsymbol{w}$:



$$\boldsymbol{p}_i = \boldsymbol{K}\,\boldsymbol{P}\,\boldsymbol{V}_i\,\boldsymbol{w}$$

Intrinsic camera matrix | Projection matrix | View matrix

$$\begin{bmatrix} x_i \\ y_i \\ w_i \end{bmatrix} = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} v_{11} & v_{12} & v_{13} & v_{14} \\ v_{21} & v_{22} & v_{23} & v_{24} \\ v_{31} & v_{32} & v_{33} & v_{34} \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

Finding homographic transformation 2/3

- A homography between two views is usually found as:

$$\boldsymbol{p}_K = \boldsymbol{K}_K \boldsymbol{P} \boldsymbol{V}_K \boldsymbol{w}$$
$$\boldsymbol{p}_i = \boldsymbol{K}_i \boldsymbol{P} \boldsymbol{V}_i \boldsymbol{w}$$

hence

$$\boldsymbol{p}_i = \boldsymbol{K}_i \boldsymbol{P} \boldsymbol{V}_i \boldsymbol{V}_K^{-1} \boldsymbol{P}^{-1} \boldsymbol{K}_K^{-1} \boldsymbol{p}_K$$

- But, $\boldsymbol{K}_K \boldsymbol{P} \boldsymbol{V}_K$ is not a square matrix and cannot be inverted
  - To find the correspondence, we need to constrain 3D coordinates $\boldsymbol{w}$ to lie on the plane:

$$\boldsymbol{N} \cdot (\boldsymbol{w} - \boldsymbol{w}_F) = 0 \quad \text{or} \quad d = \begin{bmatrix} n_x & n_y & n_z & -\boldsymbol{N} \cdot \boldsymbol{w}_F \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

Finding homographic transfo

The plane in the camera coordinates (not world coordinates)

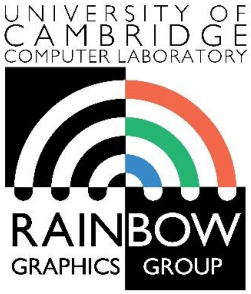
- Then, we add the plane equation to the projection matrix

$$\begin{bmatrix} x_i \\ y_i \\ d_i \\ w_i \end{bmatrix} = \begin{bmatrix} f_x & 0 & 0 & c_x \\ 0 & f_y & 0 & c_y \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ n_x^{(c)} & n_y^{(c)} & n_z^{(c)} & -\boldsymbol{N}^{(c)} \cdot \boldsymbol{w}_F^{(c)} \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} v_{11} & v_{12} & v_{13} & v_{14} \\ v_{21} & v_{22} & v_{23} & v_{24} \\ v_{31} & v_{32} & v_{33} & v_{34} \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

$$\hat{\boldsymbol{p}}_i \qquad \hat{\boldsymbol{K}}_i \qquad \hat{\boldsymbol{P}} \qquad \boldsymbol{V}_i \qquad \boldsymbol{w}$$

- Where d_i is the distance to the plane
- Hence

$$\hat{\boldsymbol{p}}_i = \hat{\boldsymbol{K}}_i \hat{\boldsymbol{P}} \boldsymbol{V}_i \boldsymbol{V}_K^{-1} \hat{\boldsymbol{P}}^{-1} \hat{\boldsymbol{K}}_K^{-1} \hat{\boldsymbol{p}}_K$$



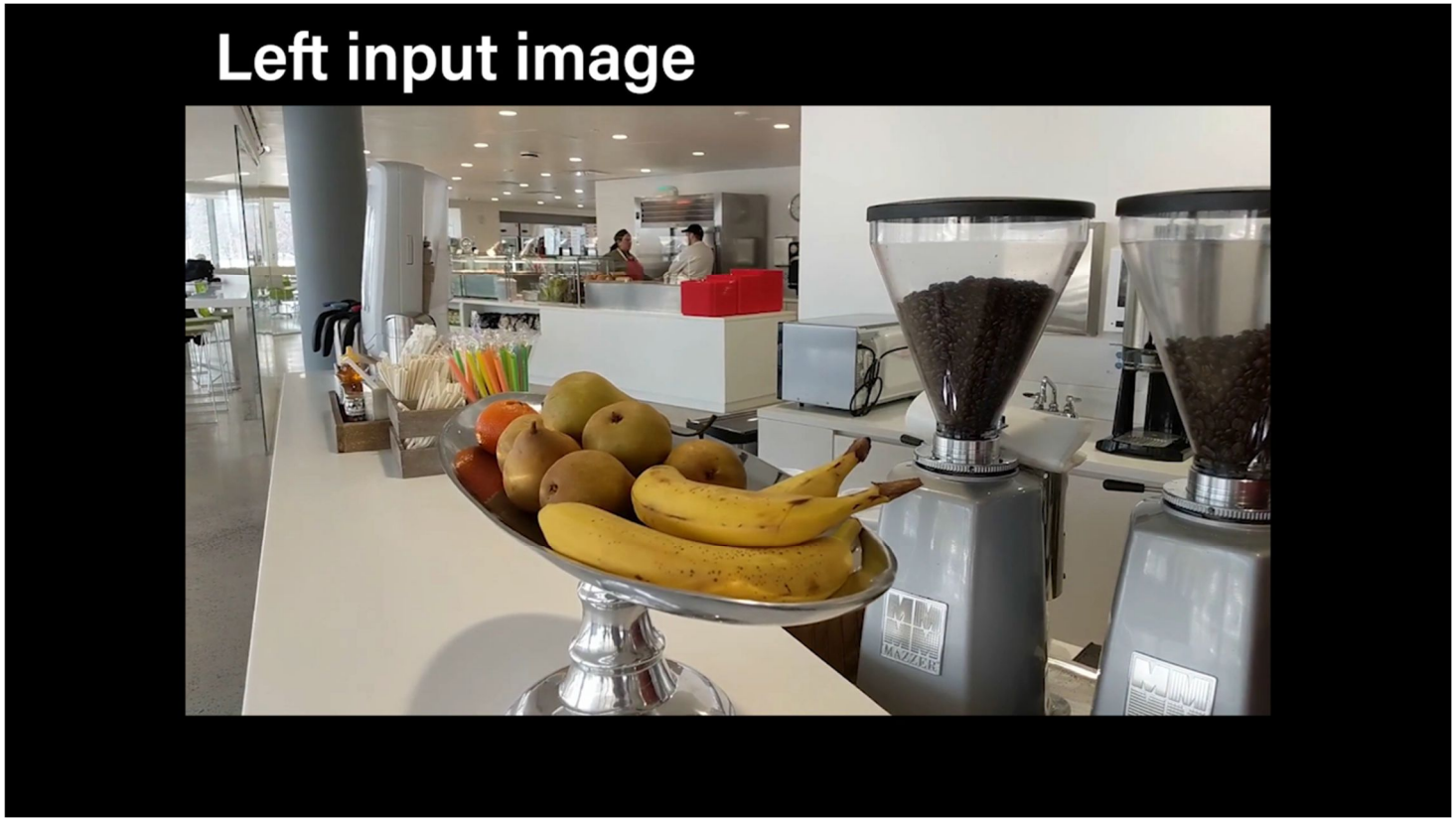
Neural radiance fields

differentiable volumetric rendering

Rafał Mantiuk
Computer Laboratory, University of Cambridge

Stereo magnification: learning view synthesis using multiplane images

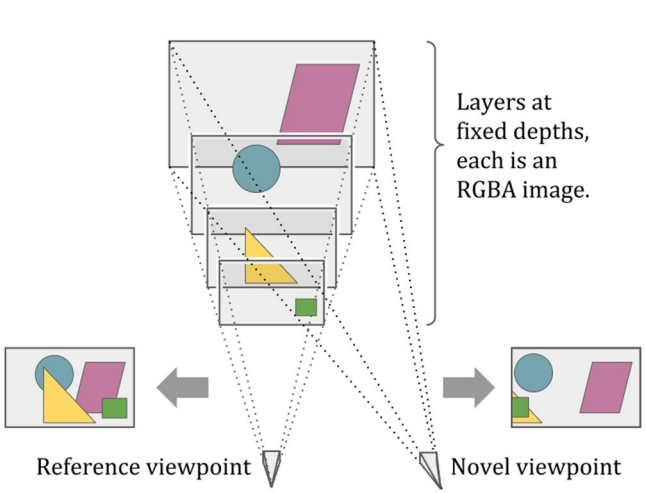
- Synthetize motion parallax from two (stereo) views

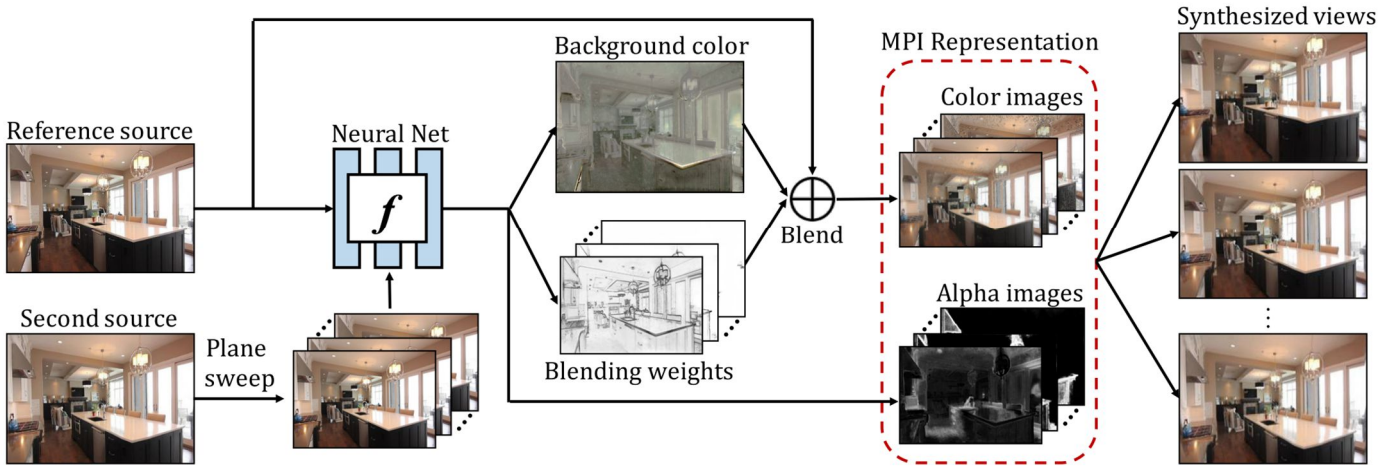


Zhou, Tinghui, Richard Tucker, John Flynn, Graham Fyffe, and Noah Snavely. "Stereo Magnification: Learning View Synthesis Using Multiplane Images." *ACM Transactions on Graphics* 37, no. 4 (August 31, 2018): 1–12. https://doi.org/10.1145/3197517.3201323.

Stereo magnification: learning view synthesis using multiplane images

- Goal: decompose images into multiple planes with an alpha channel (MPI)
- Intermediate representation: background and foreground images
  - To better handle occlusions
  - The network is overfitted to each scene

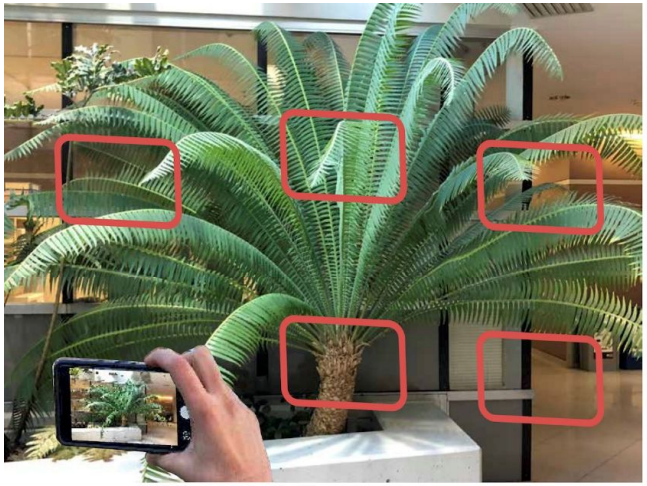




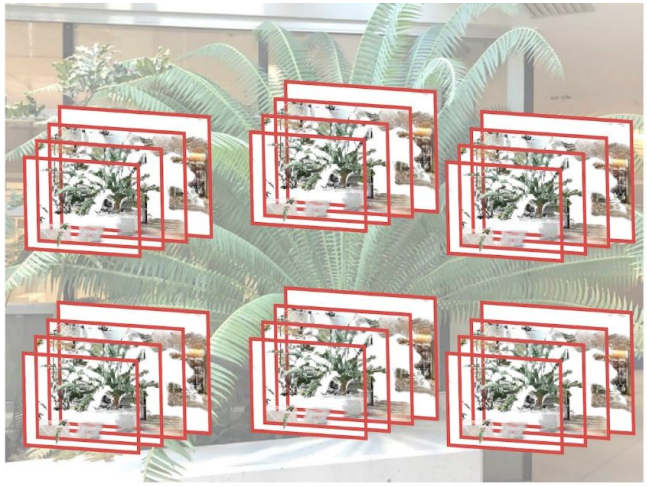
Local Light Field Fusion: Practical View Synthesis with Prescriptive Sampling Guidelines

- Reconstruct multiple MPIs, then blend them
- This is to better capture view-dependent effects
  - E.g. specular reflections

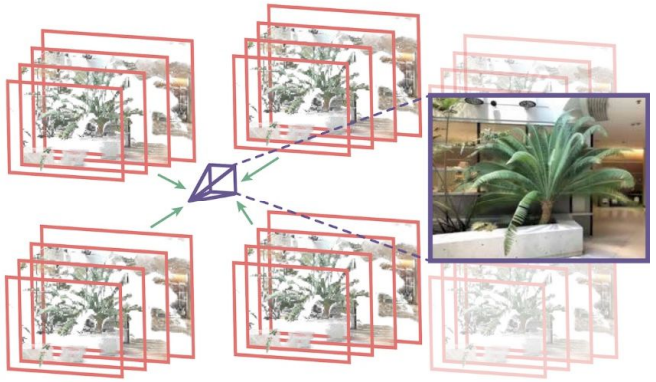
Mildenhall, Ben et al. "Local Light Field Fusion: Practical View Synthesis with Prescriptive Sampling Guidelines." *ACM Trans. on Graphics* 38, no. 4 (July 12, 2019): 1–14. https://doi.org/10.1145/3306346.3322980.



Fast and easy handheld capture with guideline: closest object moves at most D pixels between views



Promote sampled views to local light field via layered scene representation



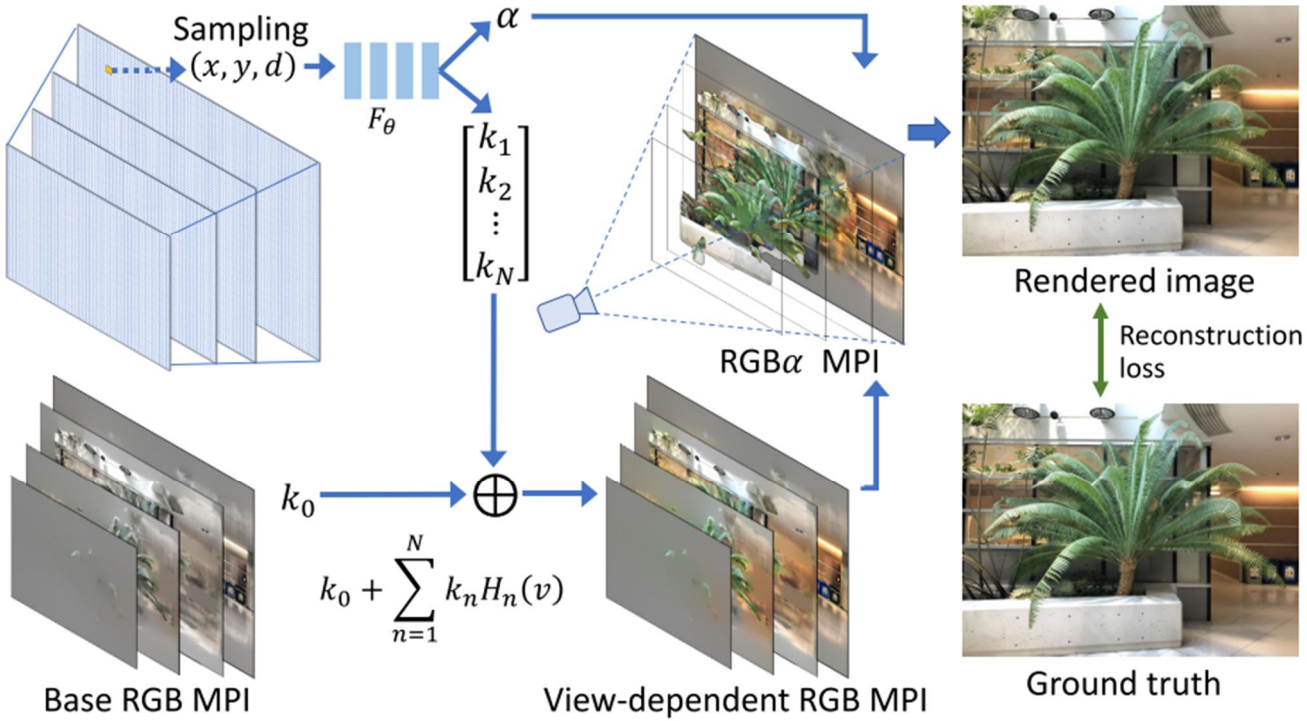
Blend neighboring local light fields to render novel views

NeX: Real-time View Synthesis with Neural Basis Expansion

- MPI + view-dependent color encoding
- High quality reproduction of the view-dependent effects
  - Specular reflections
  - Diffraction
  - …

NeX: Real-time View Synthesis with Neural Basis Expansion

- The color is encoded as a linear combination of the basis functions
- The basis functions are trainable

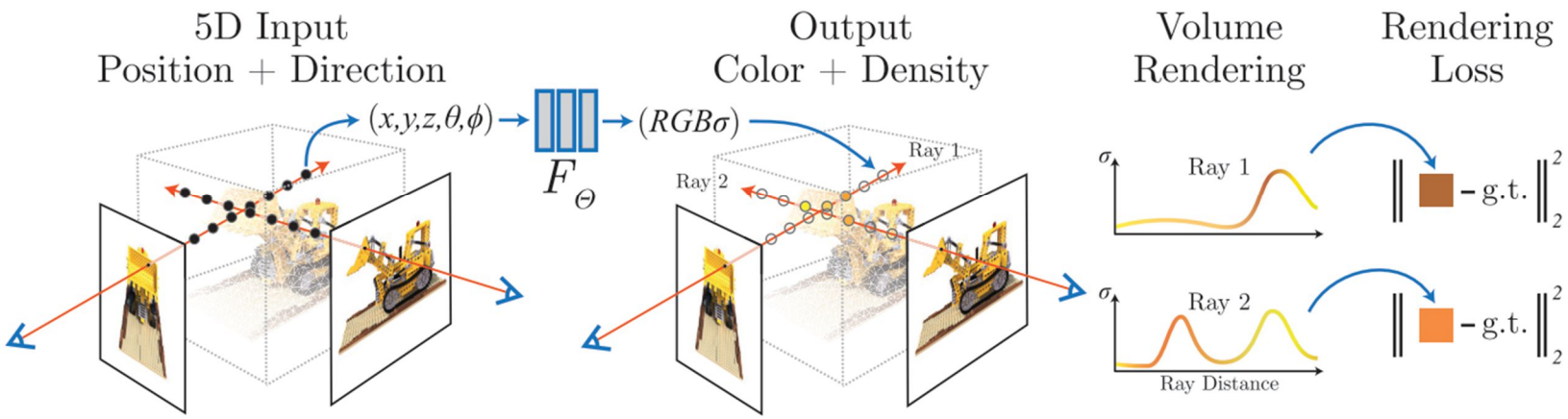


NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis

- Models a volume rather than a set of discrete planes
- 360 or front facing
- Uses MLP to represent the colour and opacity

Mildenhall, Ben, Pratul P. Srinivasan, Matthew Tancik, Jonathan T. Barron, Ravi Ramamoorthi, and Ren Ng. “NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis,” 405–21, 2020. https://doi.org/10.1007/978-3-030-58452-8_24.

NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis



Pixel colour

(x,y,z) coordinates along the ray

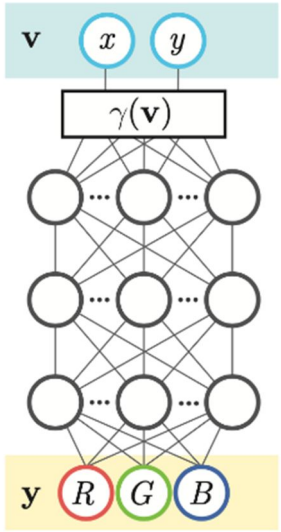
$$C(\mathbf{r}) = \int_{t_n}^{t_f} T(t)\sigma(\mathbf{r}(t))\mathbf{c}(\mathbf{r}(t), \mathbf{d})dt\,, \text{ where } T(t) = \exp\left(-\int_{t_n}^{t} \sigma(\mathbf{r}(s))ds\right)$$

Computed as a (differentiable) stratified sampling

Colour at (x,y,z) in the direction d (stored in an MLP)

"opacity" or probability of ray terminating (stored in an MPL)

Positional encoding

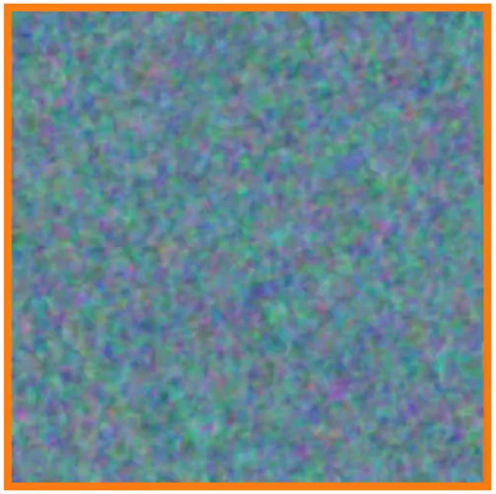


$$\gamma(p) = \left(\sin\left(2^0\pi p\right), \cos\left(2^0\pi p\right), \cdots, \sin\left(2^{L-1}\pi p\right), \cos\left(2^{L-1}\pi p\right)\right)$$

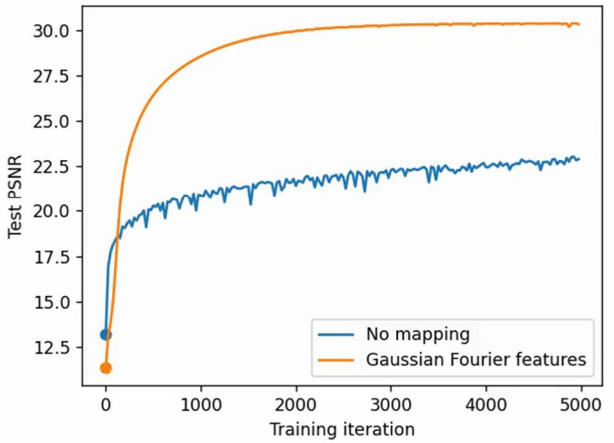
- Encoding coordinates as the Fourier "features" allows MPL to learn high frequencies
- Works with other basis functions

$$y = f(\gamma(p); w)$$

No positional encoding

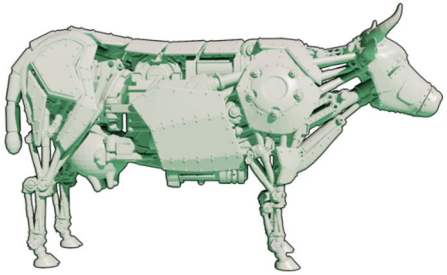


With positional encoding

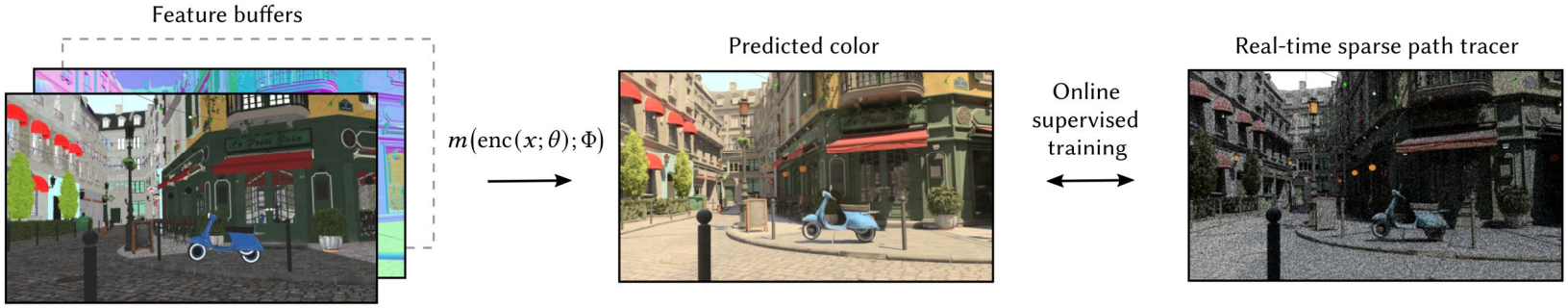


Implicit (neural) (volumetric/n-dim) representations

- Neural signed distance function
  - A function that stores a distance to a surface
  - $d = f(x, y, z; \boldsymbol{\phi})$



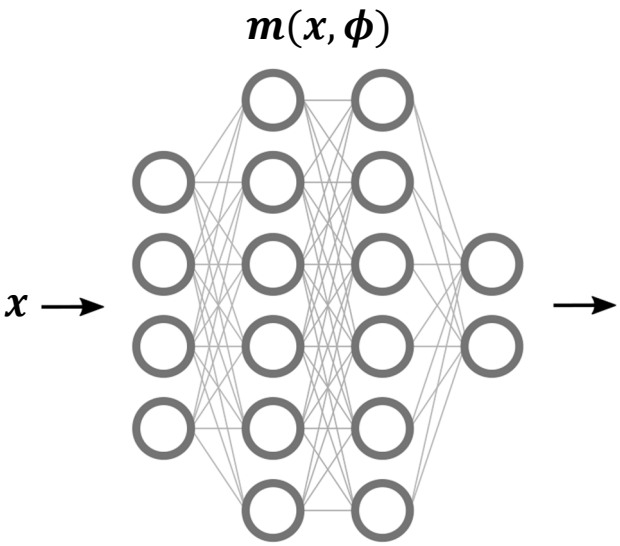
- Neural radiance caching
  - Predict colour from feature buffers independently for each pixel



- Learning a giga-pixel image
  - $RGB = f(x, y; \boldsymbol{\phi})$

Illustrations from:
https://dl.acm.org/doi/10.1145/3528223.3530127

Reducing the cost of the MLP



Given input coordinates x, only a small portion of the network activations will contribute to the output. This is inefficient.

Solution: encode a part of the information in a spatial data structure that can be directly querried, such as a (sparse) voxel grid or octree.

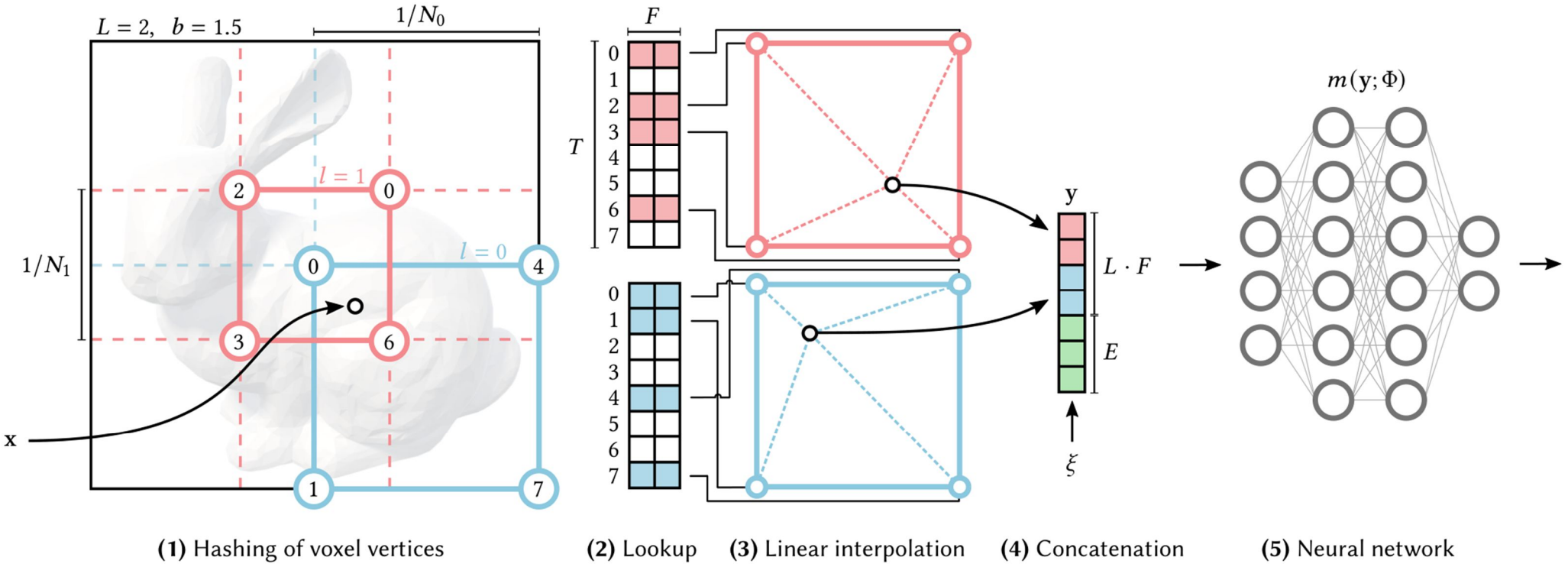
Octree
From: GPU Gems 2, Chapter 37

Tri-linear interpolation

(small) MPL

Instant neural graphics primitives with a multiresolution hash encoding

$$y = m(\gamma(x); \phi)$$



Müller, Thomas, Alex Evans, Christoph Schied, and Alexander Keller. "Instant Neural Graphics Primitives with a Multiresolution Hash Encoding." *ACM Transactions on Graphics* 41, no. 4 (July 22, 2022): 1–15. https://doi.org/10.1145/3528223.3530127.