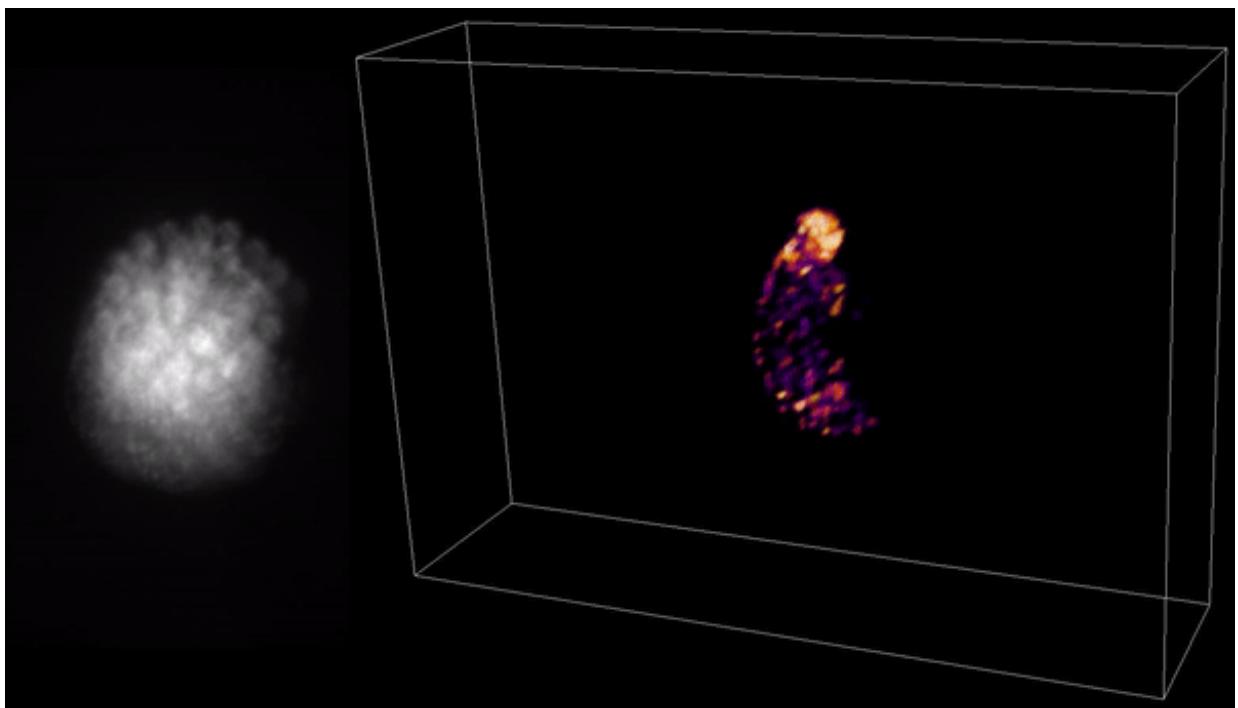




EE 046746 - Technion - Computer Vision

Elias Nehme

Tutorial 14 - Deep Computational Imaging



- [Image source](#)



Agenda

- [What is Computational Imaging?](#)
- [Compressive Imaging](#)
 - [Depth Encoding PSF](#)
- [Deep "Optics"](#)
 - [Computer Vision Pipelines](#)
 - [Differentiable Optics](#)
- [Applications](#)
- [Recommended Videos](#)
- [Credits](#)



What is Computational Imaging?

Computational Imaging

Co-design of optics, sensing, and algorithms!



💡 What is Computational Imaging?

Computational Imaging



HDR Imaging
[Mann,Devebec,Nayar,...]



Super-resolution
[Baker,Ben-Ezra,...]

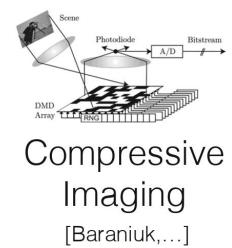


EDOF
[Dowski,Nayar,...]



Light Fields
[Levoy,...]

$$M = \begin{matrix} y & \Phi & \Psi & s \\ \Phi & \cdot & \cdot & \cdot \\ \Psi & \cdot & \cdot & \cdot \\ s & \cdot & \cdot & \cdot \end{matrix}$$



Compressive Imaging
[Baraniuk,...]



Computational Imaging



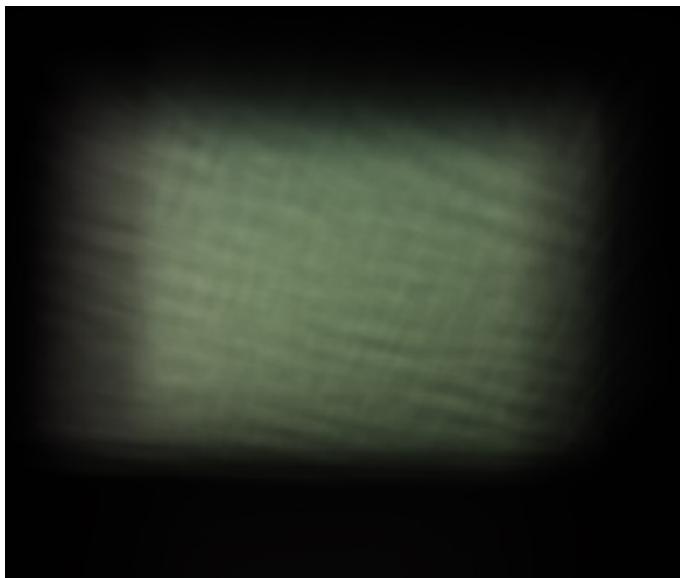
Compressive Imaging

- Depth encoding PSF



Depth Encoding PSF

- Measurement is a 2D image:

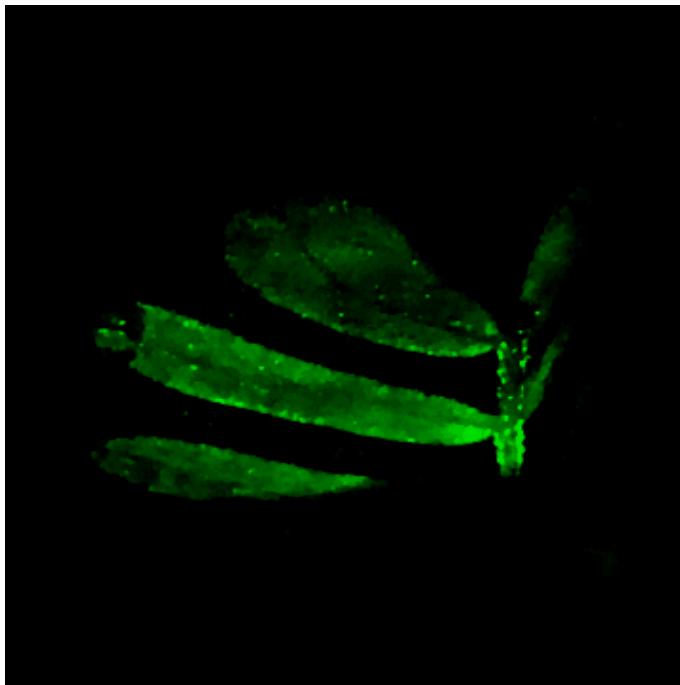


- [Image source - Optica 2018](#)



Depth Encoding PSF

- Recovery is a 3D volume:

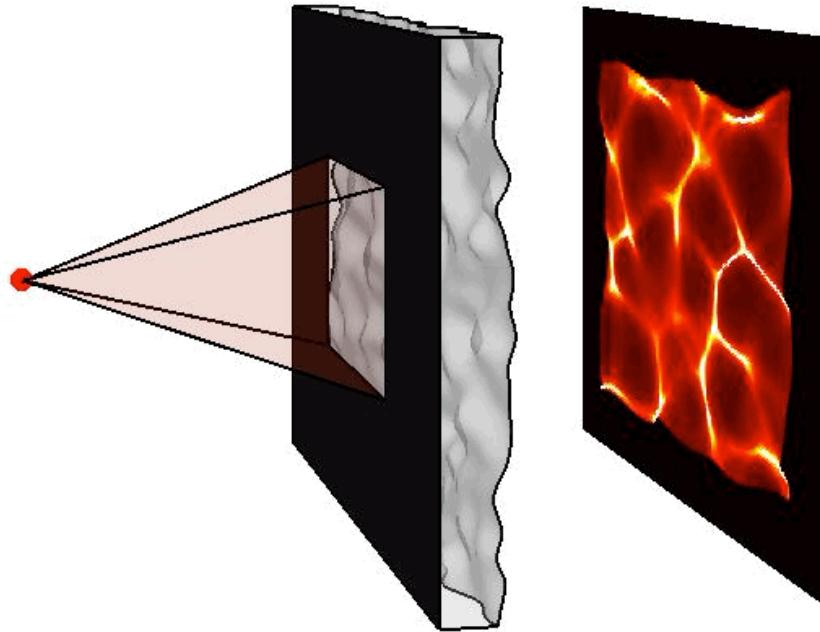


- What?? How?!
- [Image source - Optica 2018](#)



Depth Encoding PSF

- Depth Encoding Impulse Response/Point Spread Function (PSF)
 - Main idea is to encode depth in the shape generated on the 2D sensor



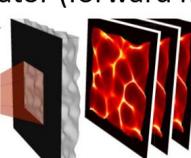
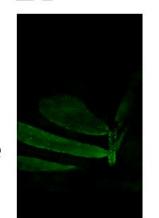
- Image source - Optica 2018



Depth Encoding PSF

- Writing down the problem in matrix formulation

$$b \in \mathbb{R}^m = H \in \mathbb{R}^{m \times d} v \in \mathbb{R}^d + e \in \mathbb{R}^m$$

Measured 2D image  Optical measurement operator (forward model)  Noise 



Depth Encoding PSF

- Solution given by "MAP" estimator under certain conditions

$$b \in \mathbb{R}^m = \begin{array}{c} \text{Low correlation} \\ H \in \mathbb{R}^{m \times d} \end{array} + e \in \mathbb{R}^m$$

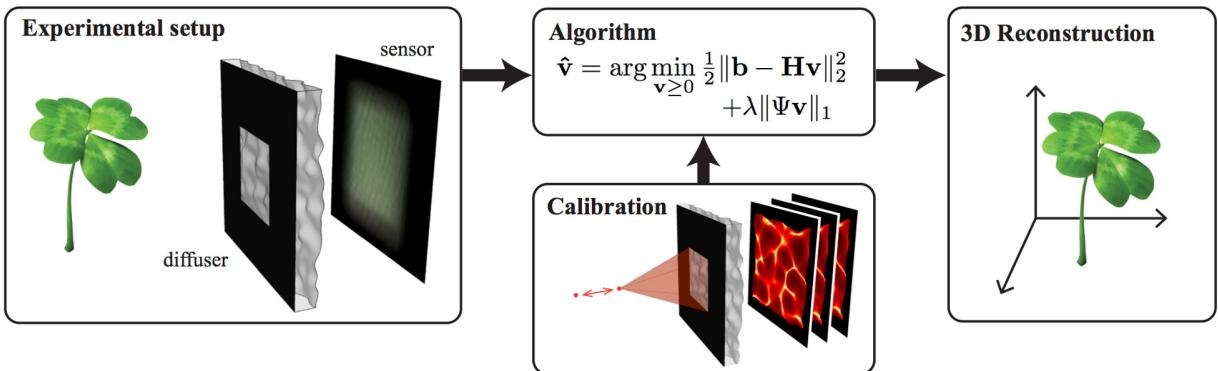
$v \in \mathbb{R}^d$
 or
 $\Psi v \in \mathbb{R}^n$ non-zeros

$$\hat{v}_{TV} = \operatorname{argmin}_{v \geq 0} \left\{ \frac{1}{2} \|b - Hv\|^2 + \lambda \|\Psi v\|_1 \right\}$$



Depth Encoding PSF

- Overall framework:



- [Image source - Optica 2018](#)



Deep Optics

- Computer Vision Pipelines
- Differentiable Optics



Computer Vision Pipelines



Computer Vision Pipelines

How do CV pipelines work?



Computer Vision Pipelines

Objective: Solve CV problem on scene

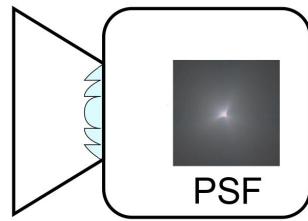


What is this?



Computer Vision Pipelines

Step 1: Build camera

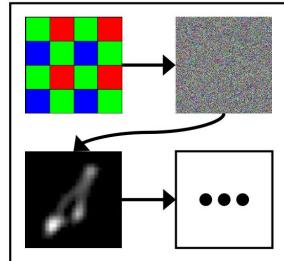


Optimize optics to minimize aberrations:
Blur/spot size, chromatic aberrations, distortions, ...



Computer Vision Pipelines

Step 2: Image Signal Processing (ISP)

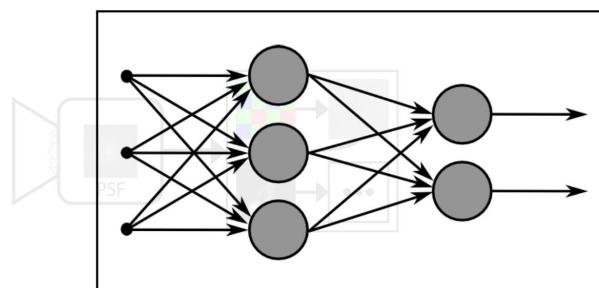


Maximize PSNR:
Demosaicking, Denoising, Deblurring, ...



Computer Vision Pipelines

Step 3: CNN for Semantic task

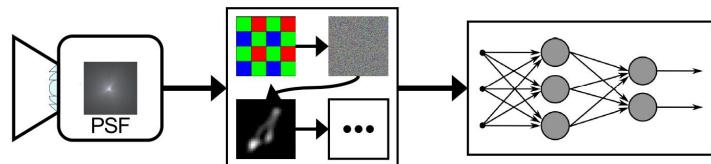


Minimize semantic loss:
classification error, segmentation error, ...



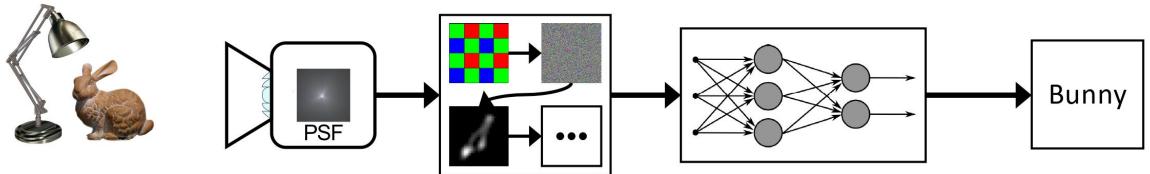
Computer Vision Pipelines

...



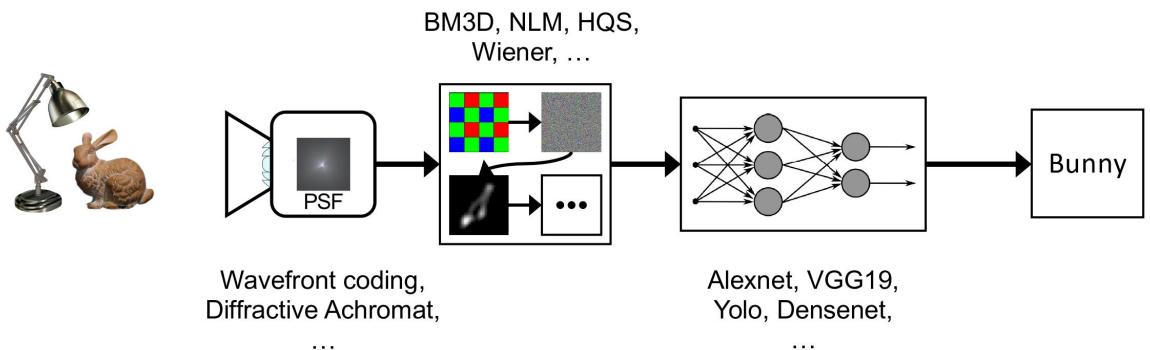
Computer Vision Pipelines

It works!



Computer Vision Pipelines

Prior work on optimizing each part of pipeline



Computer Vision Pipelines



Applications are
different, cameras &
ISPs are not



Computer Vision Pipelines

- Animal vision is adapted to the surrounding and the day-to-day "task"

Courtesy of Michael Bok



Courtesy of CSIR Notes



Courtesy of Jeffrey Beach

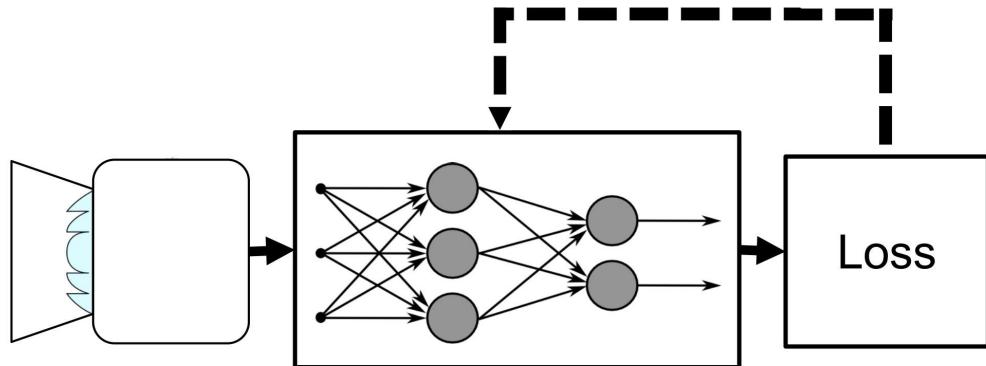


Courtesy of Microdact



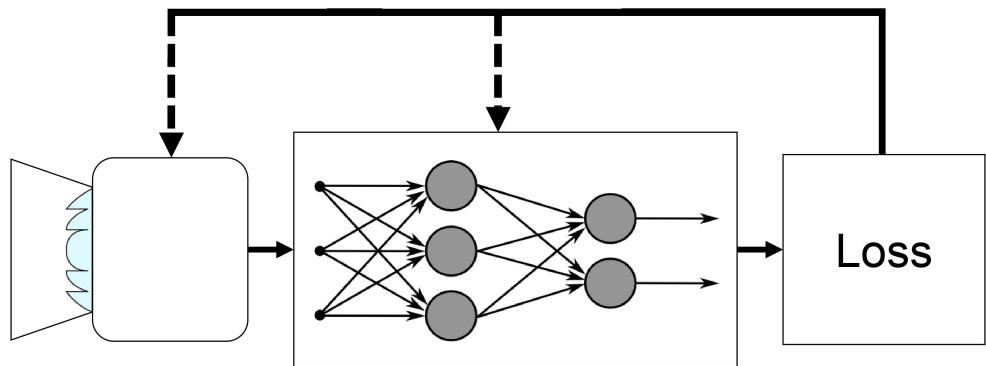
Computer Vision Pipelines

- "Standard" deep image processing



Computer Vision Pipelines

- Deep computational imaging

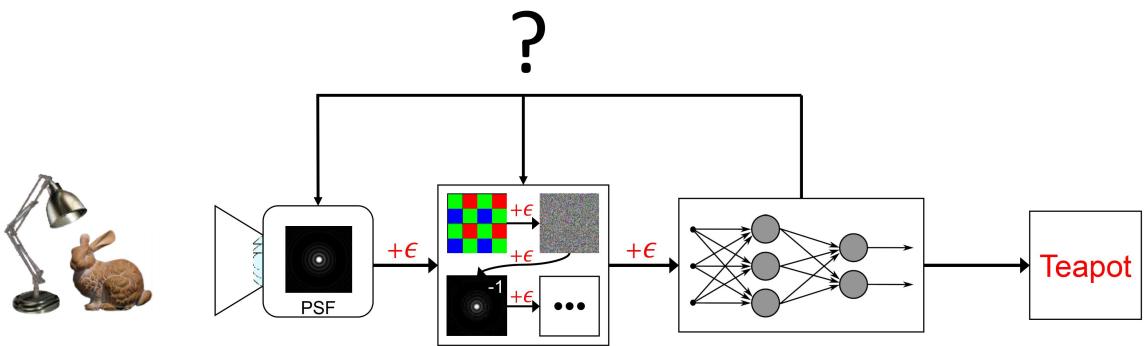


Optimize optics end-to-end with higher-level processing!



Computer Vision Pipelines

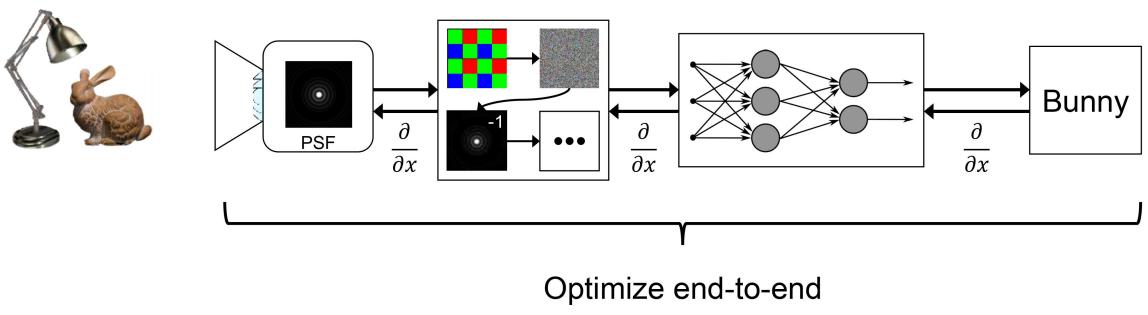
- Image classification with specialized "optics"



Computer Vision Pipelines

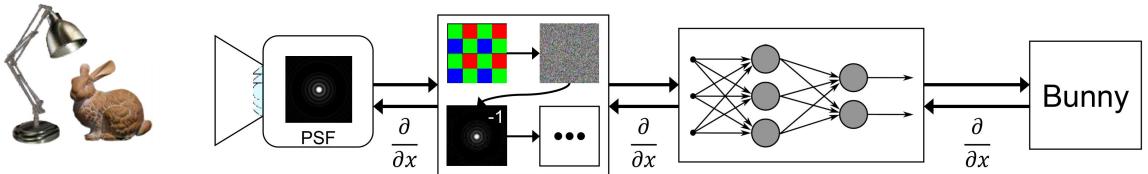
- Main idea: optimize the optics and the algorithm jointly to excel in the final task

Vision: The Deep Computational Camera

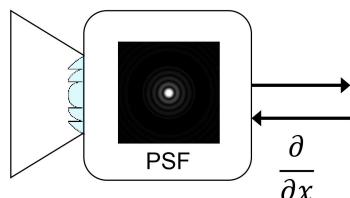


Computer Vision Pipelines

Vision: The Deep Computational Camera



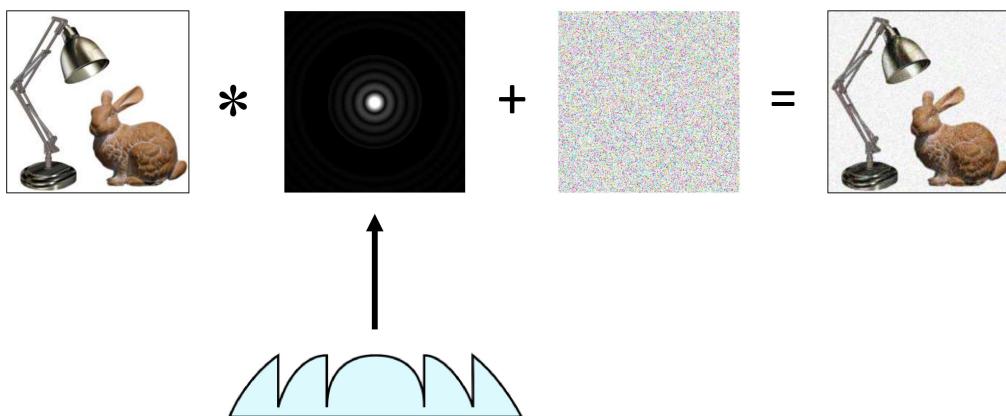
- Performance & robustness gains
- Domain-specific hardware may reduce footprint, cost, power...
- New design space: The “BunnyCam”



A differentiable optics model

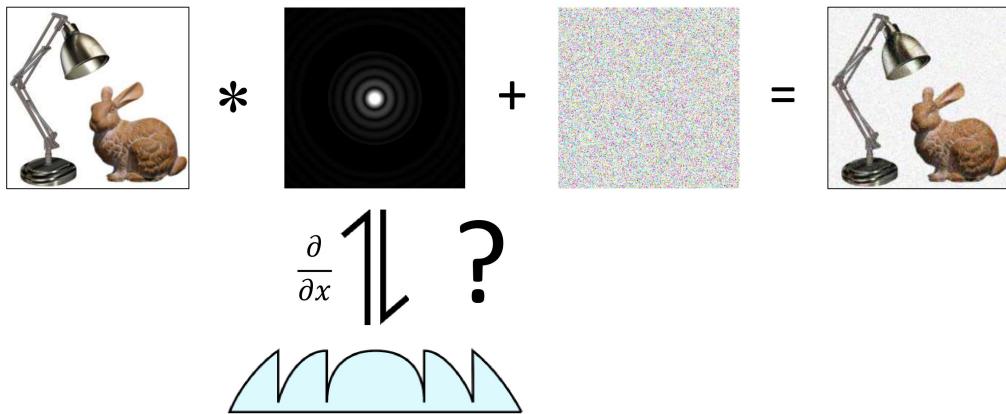


Image formation model

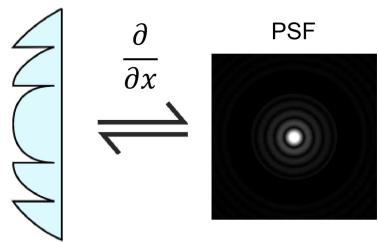


Differentiable Optics

How does the optical element map to the PSF?



Differentiable Optics

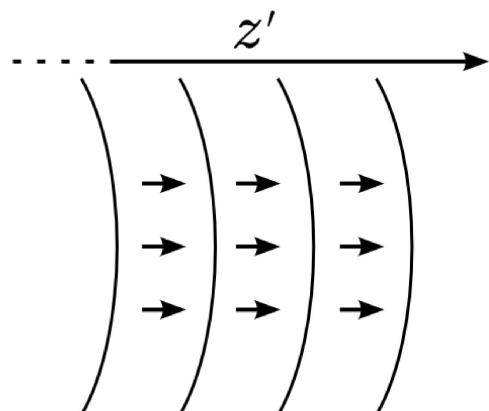


Wave Optics PSF simulator



Differentiable Optics

Spherical wave from point source

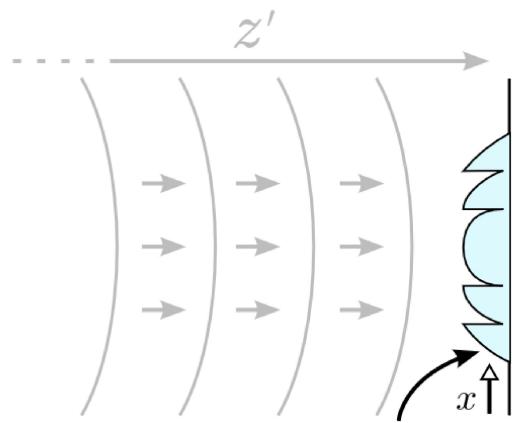


$$\exp(jk\sqrt{x^2 + z'^2})$$



Differentiable Optics

Phaseshift by optical element

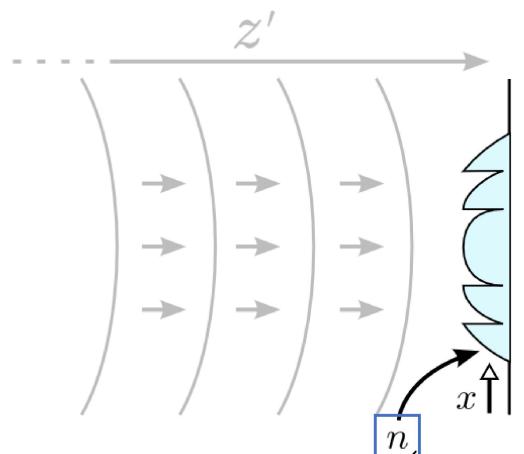


$$U(x) = \exp\left(jk\left(\sqrt{x^2 + z'^2} + (n - 1)\Phi(x)\right)\right)$$



Differentiable Optics

Phaseshift by optical element

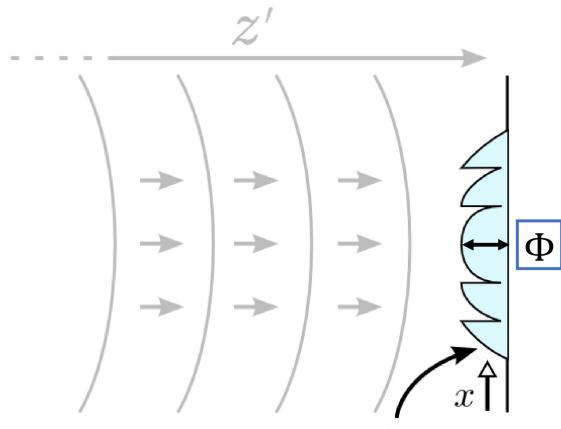


$$U(x) = \exp\left(jk\left(\sqrt{x^2 + z'^2} + [n] - 1)\Phi(x)\right)\right)$$



Differentiable Optics

Phaseshift by optical element

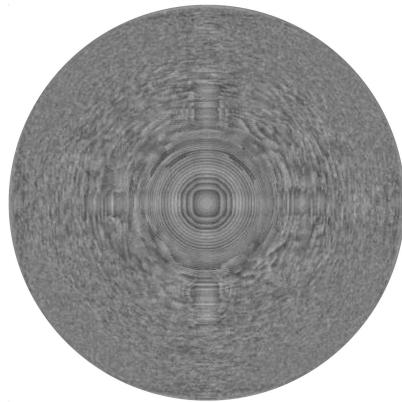


$$U(x) = \exp\left(jk\left(\sqrt{x^2 + z'^2} + (n - 1)\Phi(x)\right)\right)$$



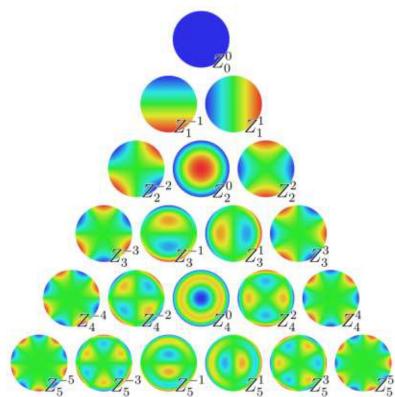
Differentiable Optics

Height Map parameterization
(diffractive)



$$\Phi[x] = [[a_{11}, a_{12}, \dots], \dots]$$

Zernike basis parameterization
(refractive)

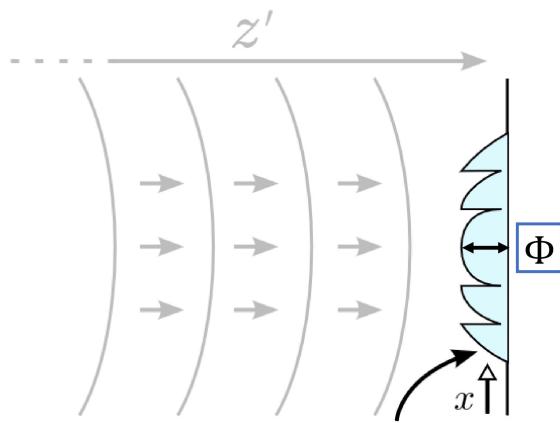


$$\Phi[x] = \sum Z_i^j[x] \cdot a_{ij}$$



Differentiable Optics

Phaseshift by optical element

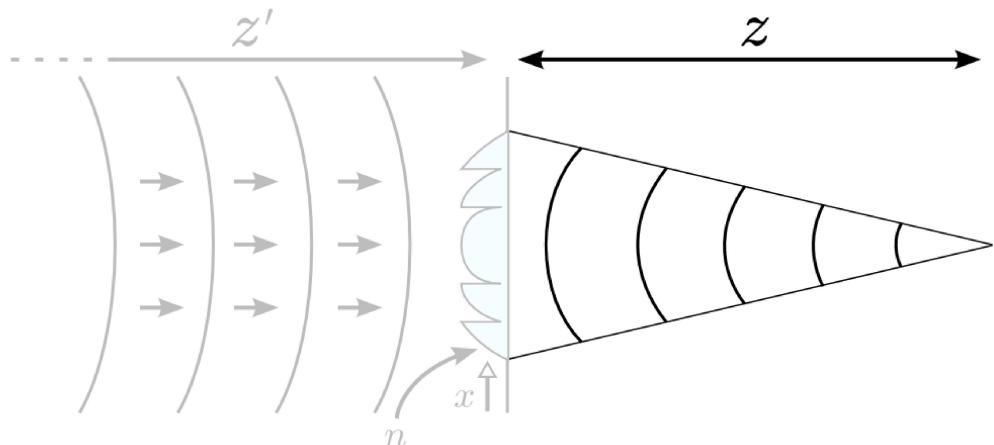


$$U(x) = \exp\left(jk\left(\sqrt{x^2 + z'^2} + (n - 1)\Phi(x)\right)\right)$$



Differentiable Optics

Fresnel propagation to sensor

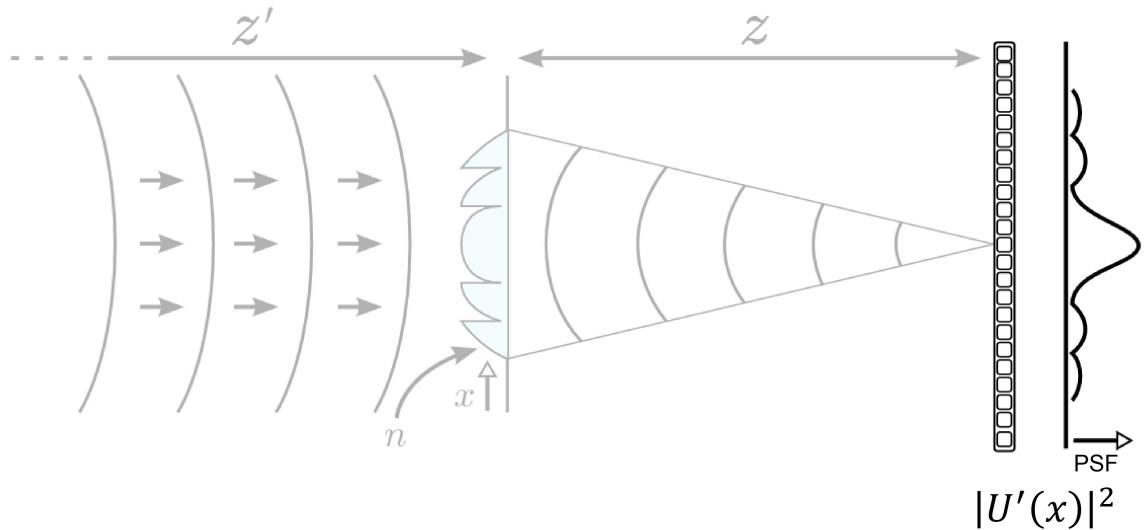


$$U'(x) = U(x) * \exp\left(\frac{jk}{2z}x^2\right)$$



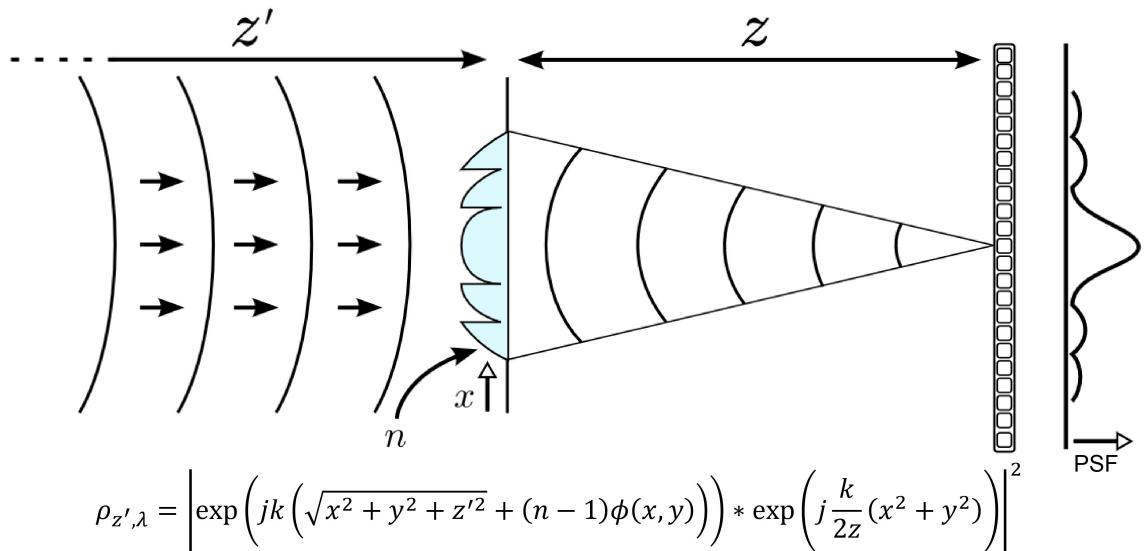
Differentiable Optics

Intensity measurement at sensor



Differentiable Optics

Calculating the PSF



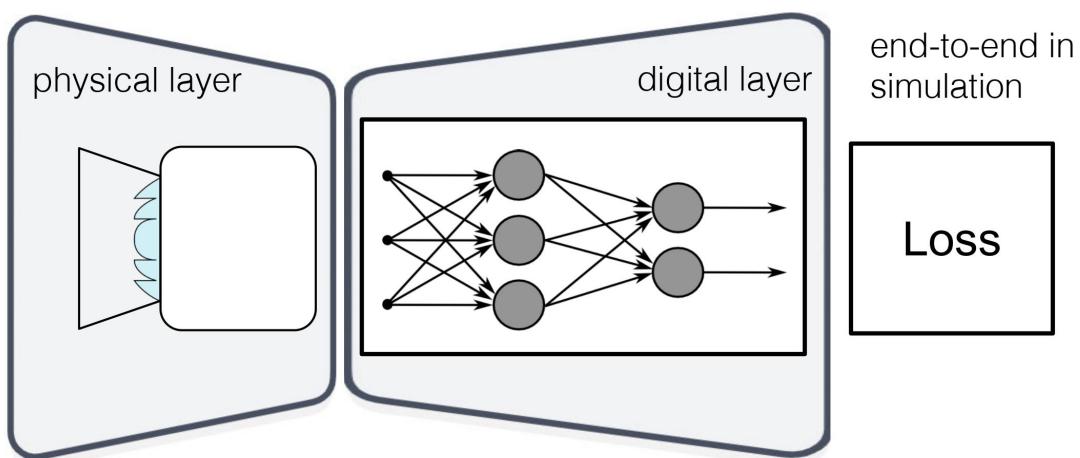
$$\rho_{z',\lambda} = \left| \exp \left(jk \left(\sqrt{x^2 + y^2 + z'^2} + (n - 1)\phi(x, y) \right) \right) * \exp \left(j \frac{k}{2z} (x^2 + y^2) \right) \right|^2$$



Differentiable Optics

Deep Optics

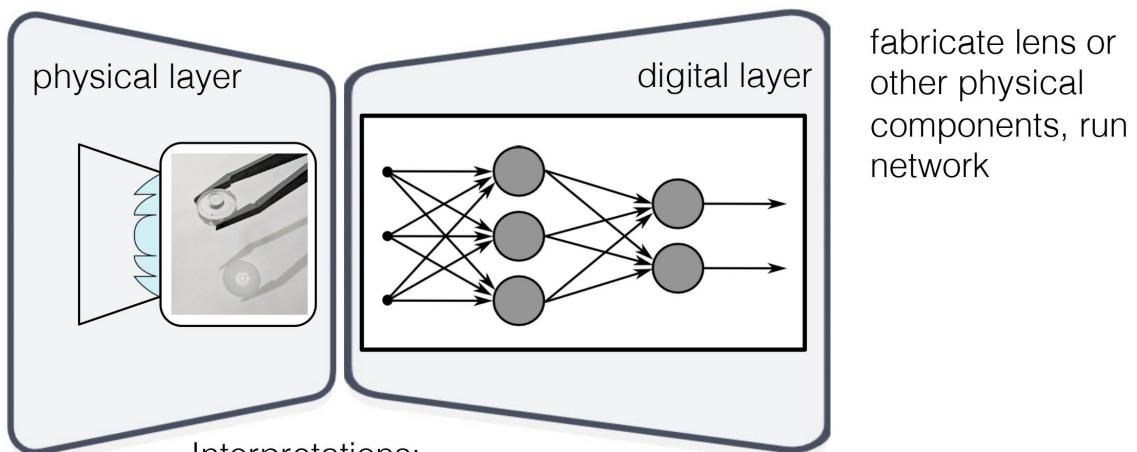
Training:



Differentiable Optics

Deep Optics

Inference:



Interpretations:

- Optical encoder, electronic decoder system
- Hybrid optical-electronic neural network

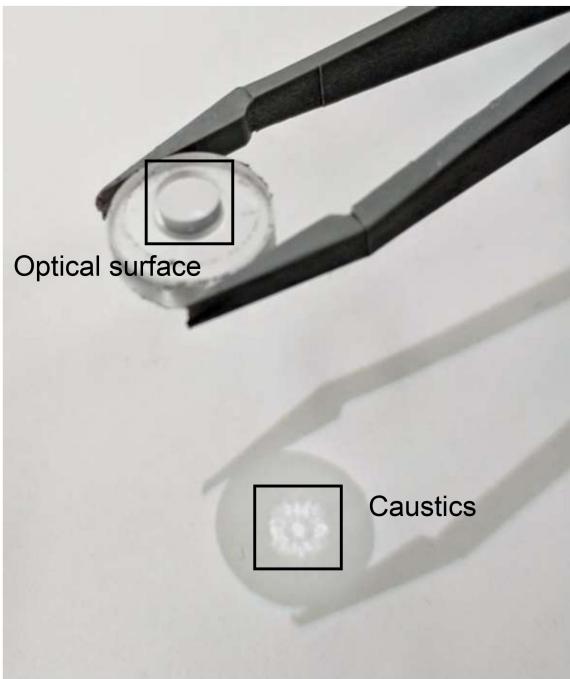


Applications

- Extended Depth of Field
- Monocular Depth Estimation / Depth from Defocus
- High Dynamic Range Imaging
- Video Compressive Sensing
- Computational Microscopy (Will not show examples)



Application 1: Extended Depth of Field (EDOF)



Refractive Achromatic EDOF element

- Polymethyl methacrylate (PMMA)
- 5 mm aperture size
- Sensor distance 35.5mm
- F-number 7.1
- One active optical surface
- Feature size $3.69\mu m$

- [Image source - ACM SIGGRAPH 2018](#)

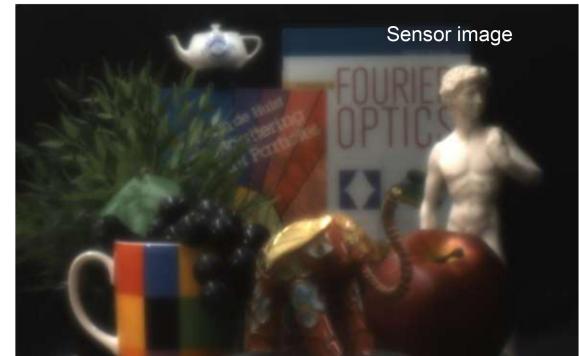


Application 1: Extended Depth of Field (EDOF)

Test scene



Regular bi-convex lens



Optimized lens

Elephant (0.5m) ➡ Book (2.0m)

- [Image source - ACM SIGGRAPH 2018](#)



Application 1: Extended Depth of Field (EDOF)

Test scene



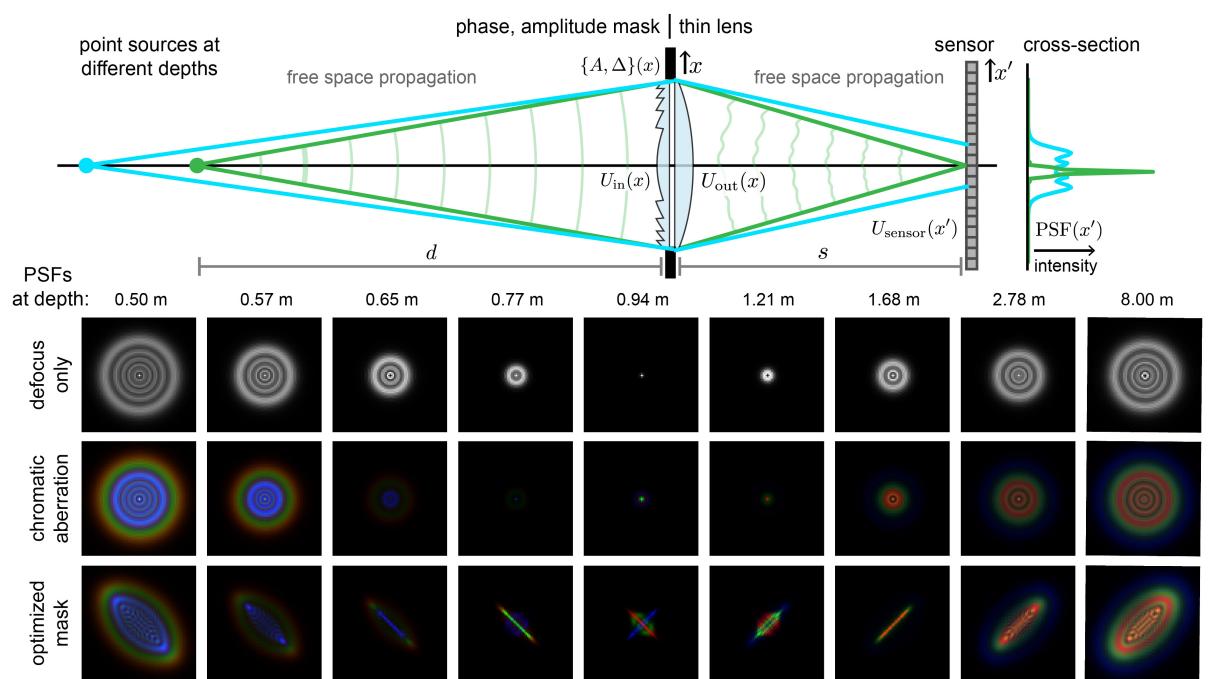
Regular bi-convex lens

Optimized lens

Elephant (0.5m) Book (2.0m)

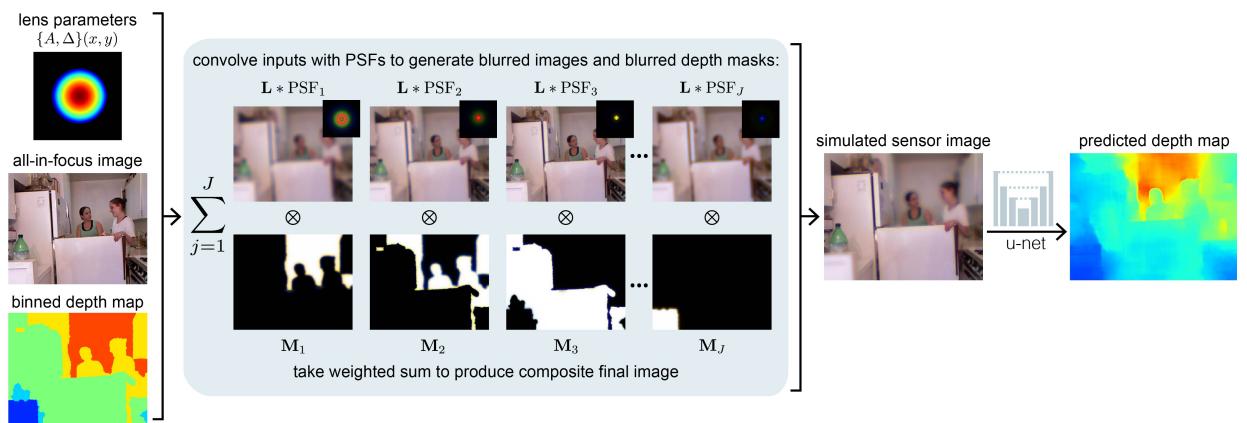
- Image source - ACM SIGGRAPH 2018

► Application 2: Monocular Depth Estimation



- Image source - ICCV 2019

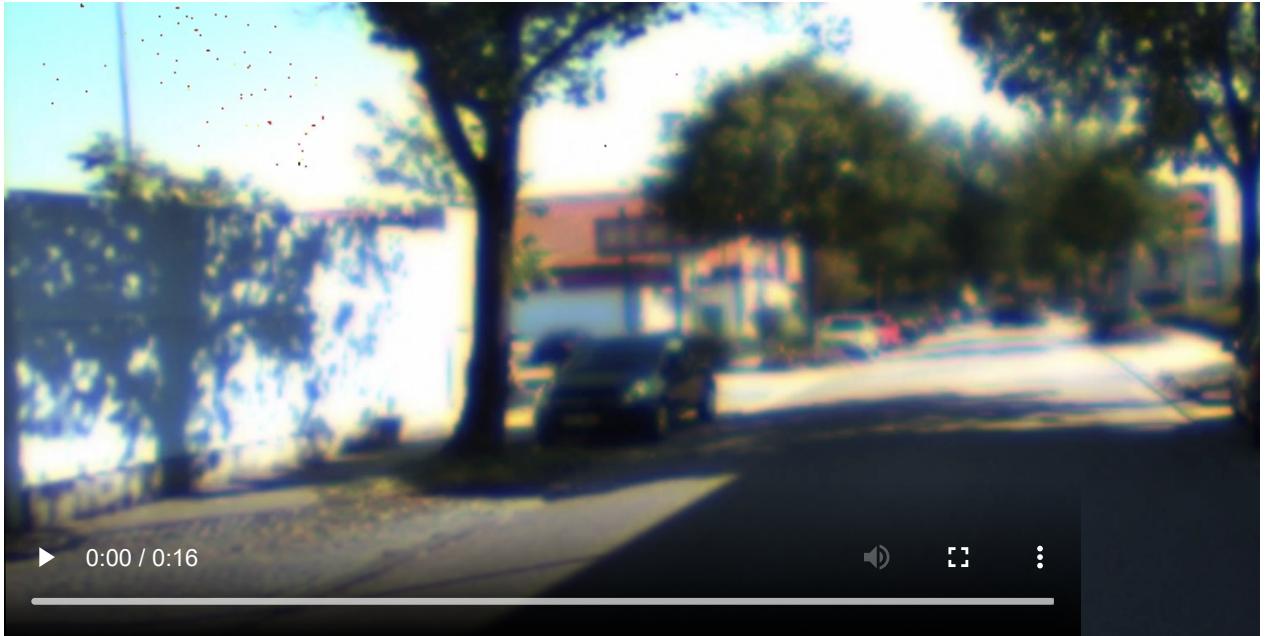
► Application 2: Monocular Depth Estimation



- [Image source - ICCV 2019](#)

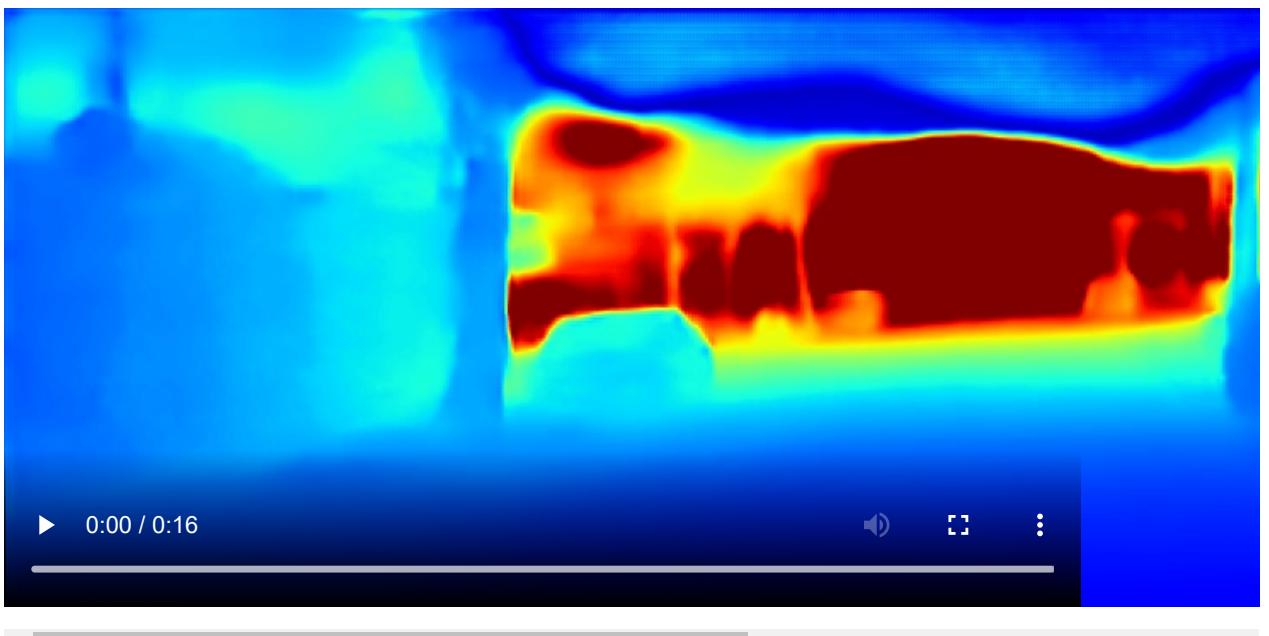
```
In [12]: from IPython.display import Video
Video("./assets/input_vid_dfd.mp4")
```

Out[12]:



```
In [10]: Video("./assets/output_vid_dfd.mp4")
```

Out[10]:

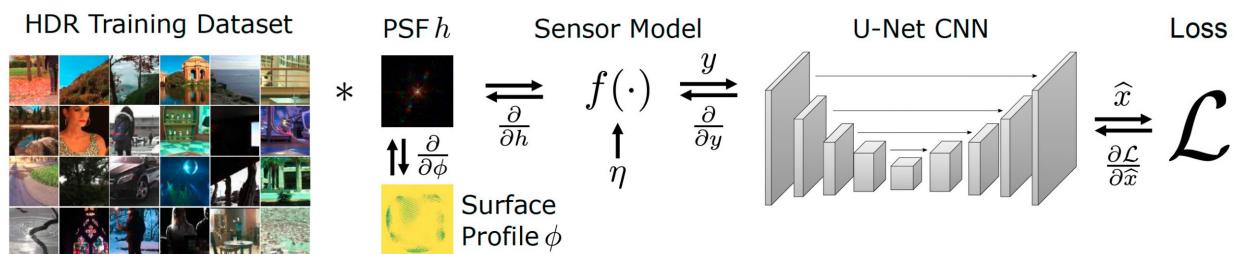


In [13]: `Video("./assets/bb_3d.mp4")`

Out[13]:



Application 3: High Dynamic Range Imaging

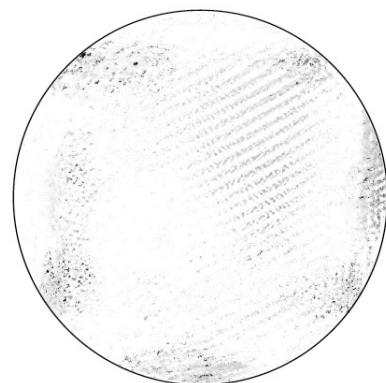


- [Image source - CVPR 2020](#)

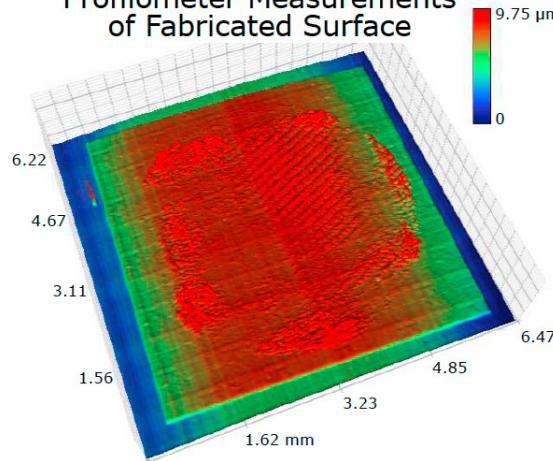


Application 3: High Dynamic Range Imaging

Optimized Height Profile



Profilometer Measurements of Fabricated Surface



Simulated PSF



Captured PSF

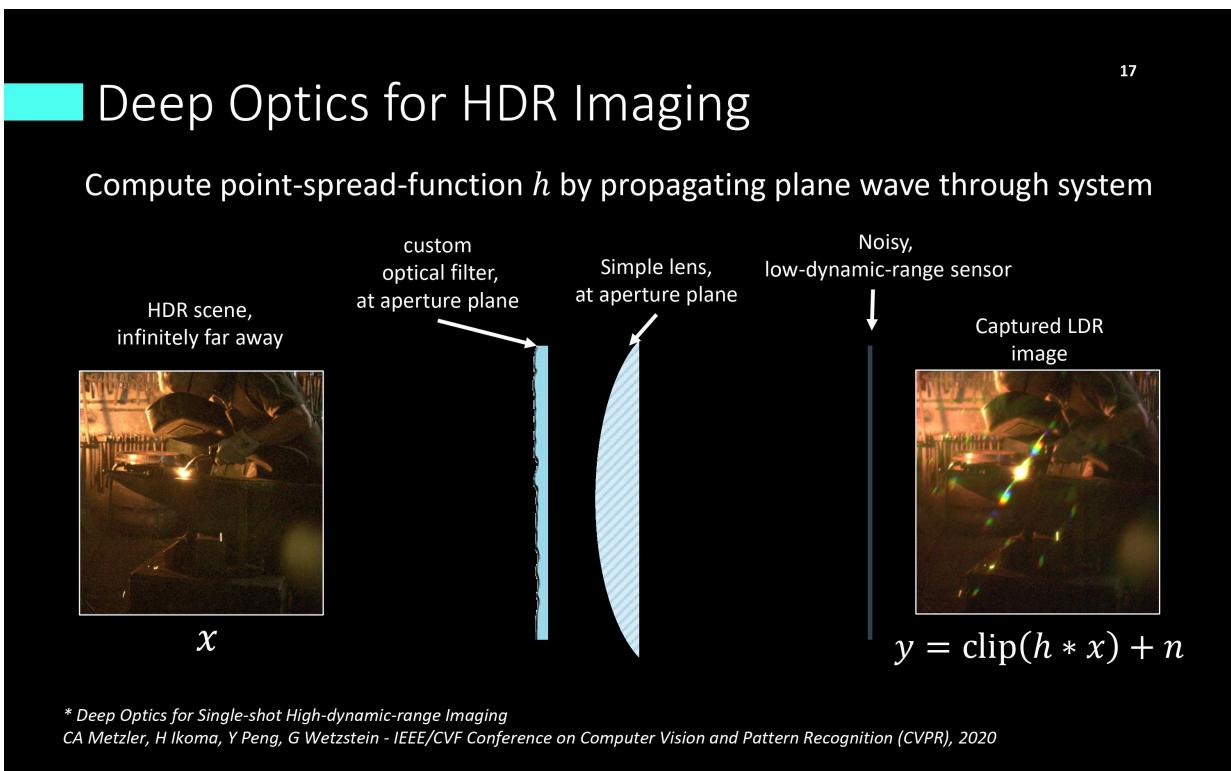


- [Image source - CVPR 2020](#)



Application 3: High Dynamic Range Imaging

17

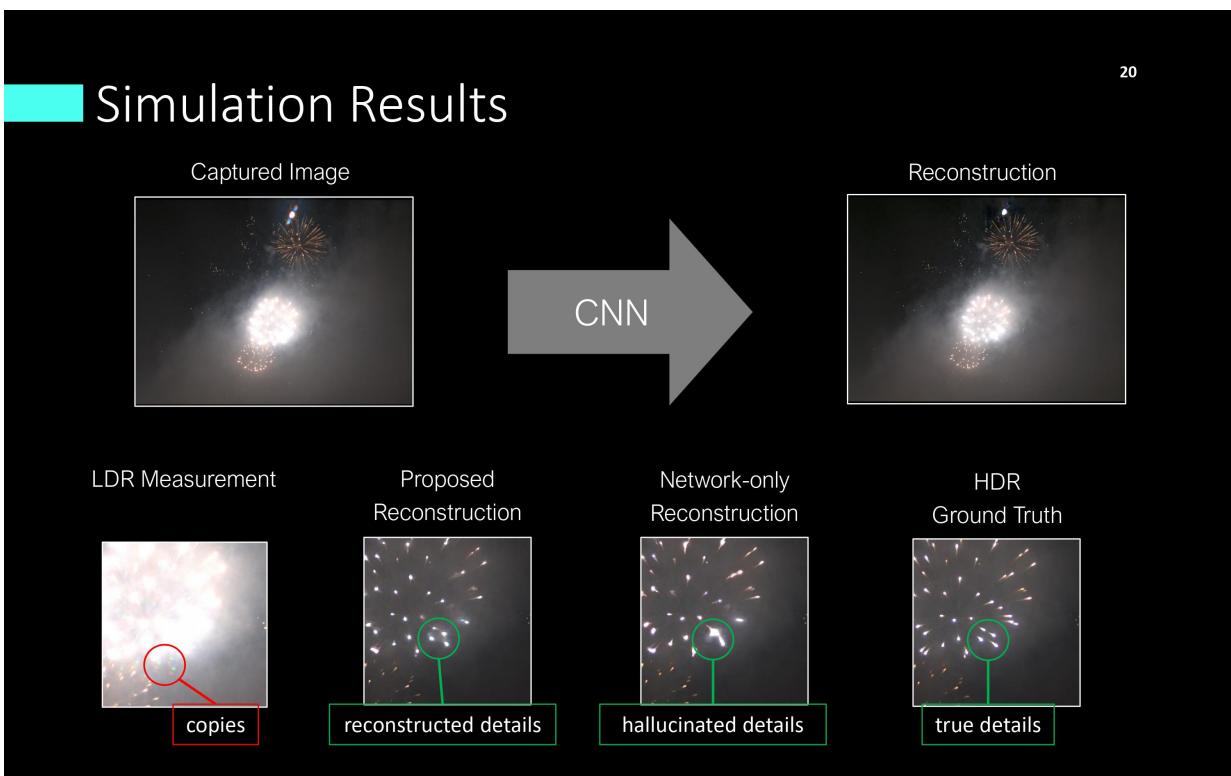


- Image source - CVPR 2020



Application 3: High Dynamic Range Imaging

20

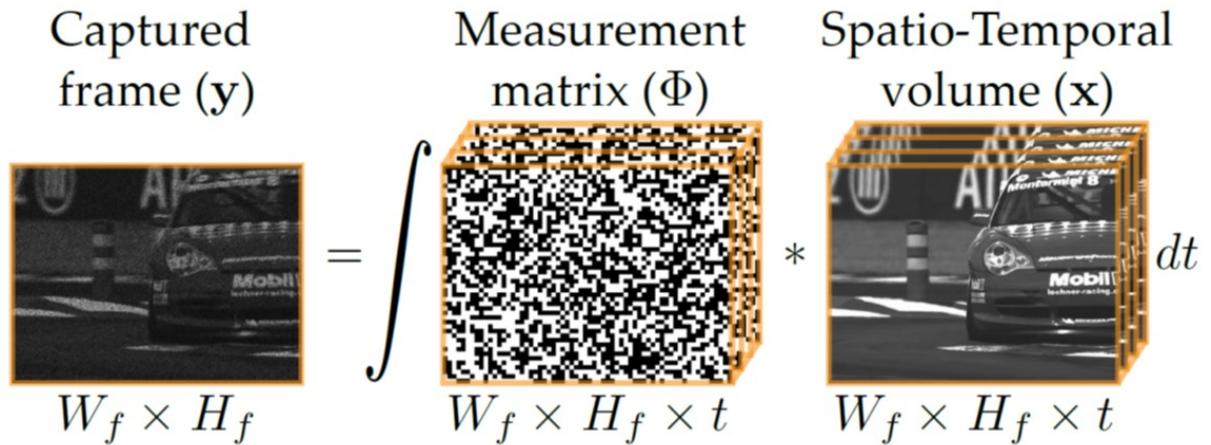


- Image source - CVPR 2020



Application 4: Video Compressive Sensing

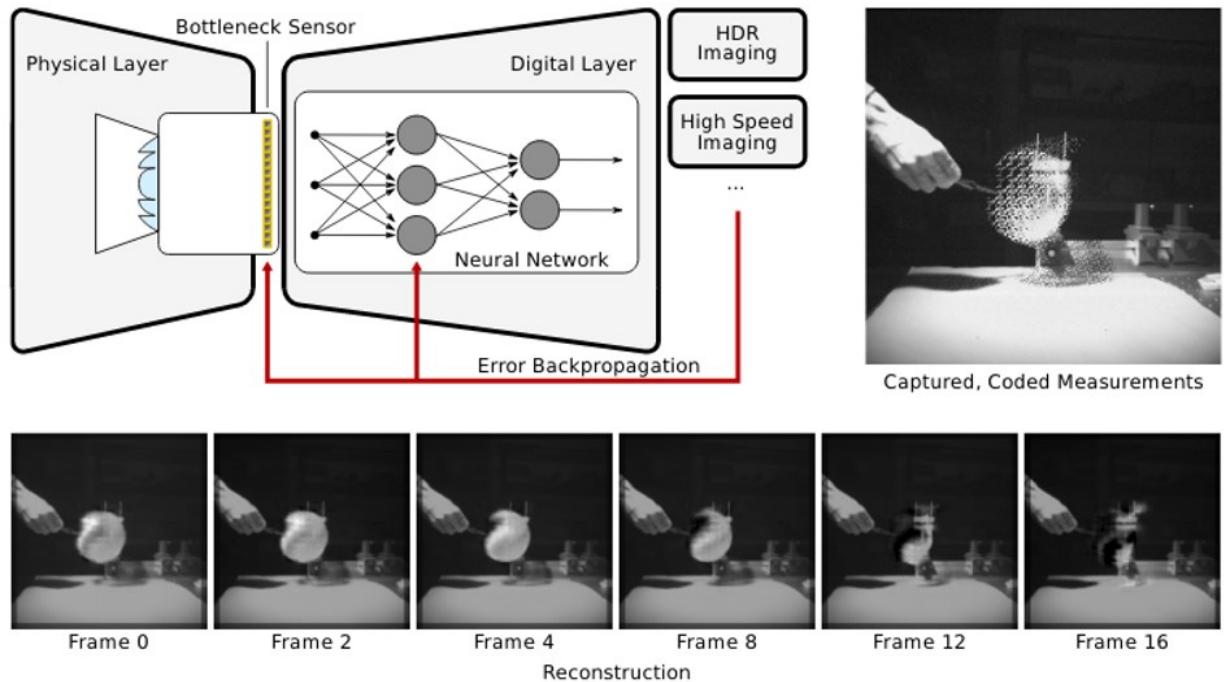
- Challenge is to learn the binary masks Φ to recover video x from snapshot y



- Image source - DSP Magazine 2020



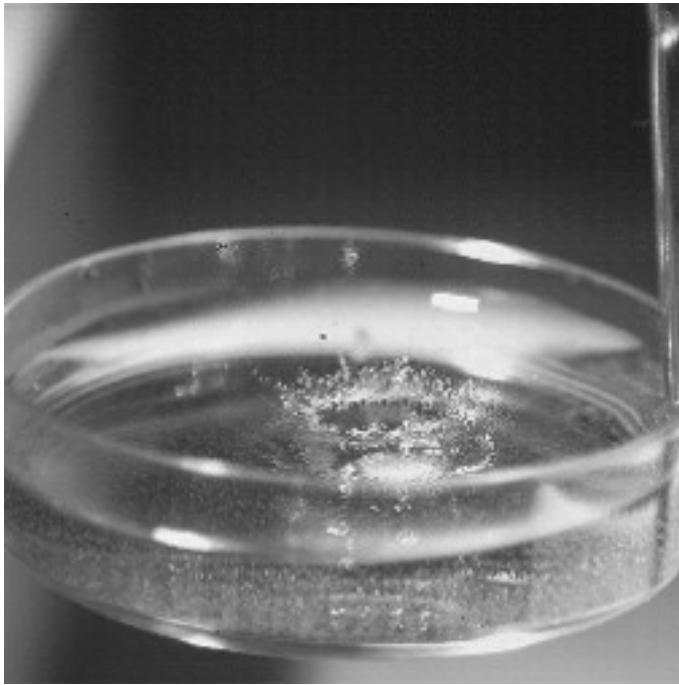
Application 4: Video Compressive Sensing



- Image source - ICCP 2020



Application 4: Video Compressive Sensing

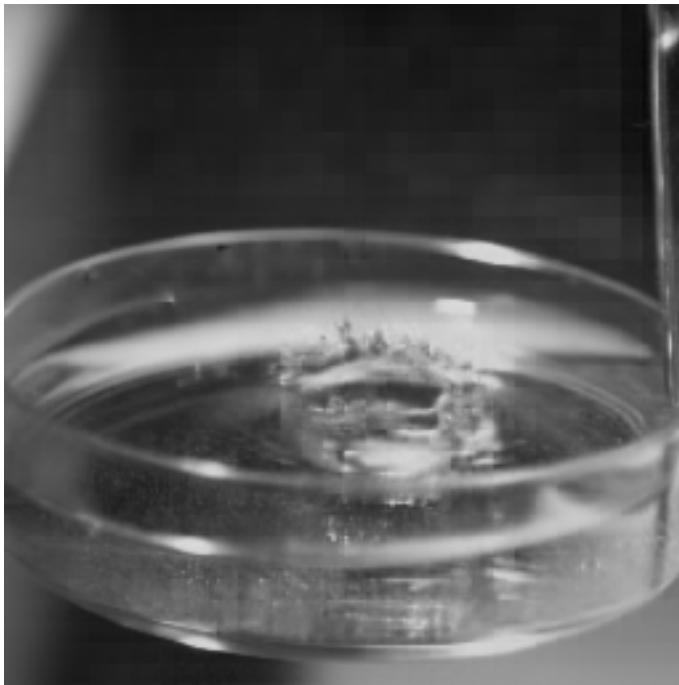


- [Image source - ICCP 2020](#)



Application 4: Video Compressive Sensing

- 64 frames recovered from 4 measurements (16 frames/capture)



- [Image source - ICCP 2020](#)



Available resources online

- <https://github.com/computational-imaging/opticalCNN>
- <https://github.com/vsitzmann/deepphotics>
- <https://github.com/computational-imaging/DeepOpticsHDR>
- <https://github.com/EliasNehme/DeepSTORM3D>

- <https://github.com/computational-imaging/DepthFromDefocusWithLearnedOptics>
- etc.



Recommended Videos



Warning!

- These videos do not replace the lectures and tutorials.
- Please use these to get a better understanding of the material, and not as an alternative to the written material.

Video By Subject

- End-to-end Optimization of Optics and Image Processing - [Vincent Sitzmann](#)
- Neural Sensors - [J.N.P Martel](#)
- High Dynamic Range Imaging - [Christopher Metzler](#)
- 3D Single Molecule Localization Microscopy - [Elias Nehme](#)
- Towards Neural Imaging & Signal Processing - [Gordon Wetzstein](#)



Credits

- [End-to-end optimization of optics and image processing](#) - Vincent Sitzmann
- [ACM SIGGRAPH 2020 Courses](#) - Yifan (Evan) Peng, Ashok Veeraraghavan, Wolfgang Heidrich, Gordon Wetzstein
- [Stanford EE367/CS448I](#) (Computational Imaging and Display) - Gordon Wetzstein
- [IEEE SPACE Webinar](#) - IEEE Computational Imaging TC
- Research papers:
 - [End-to-end optimization of optics and image processing for achromatic extended depth of field and super-resolution imaging](#)
 - [Deep Optics for Monocular Depth Estimation and 3D Object Detection](#)
 - [Deep Optics for Single-shot High-dynamic-range Imaging](#)
 - [Neural Sensors: Learning Pixel Exposures for HDR Imaging and Video Compressive Sensing With Programmable Sensors](#)
 - [Convolutional neural networks that teach microscopes how to image](#)
 - [DeepSTORM3D: dense 3D localization microscopy and PSF design by deep learning](#)
 - [Depth From Defocus With Learned Optics](#)
 - etc.
- Icons from [Icon8.com](#) - <https://icon8.com>