Deep Learning Tomography

Lecture 9b

Outline

- Optical Diffraction Tomography Introdution (ODT)
- Machine Learning for ODT
  1. TomoNet
     - accounts for the missing cone problem
  2. MaxwellNet
     - physics informed neural network
- Microfluidic Implementation

3D rendering

- https://www.chaos.com/blog/what-is-3d-rendering-guide-to-3d-visualization

3D rendering versus 3D inverse scattering

- Rendering: Realistic 2D projections from 3D computer model
- Inverse scattering: 3D reconstruction from 2D measurements

First step: to digitize the "Archivio di Stato"

Two main challenges:

- Huge amount of manuscripts

  <u>80 km</u> of documents

  - Birth and death records
  - Testaments
  - Tax declarations
  - Commercial transactions
  - Work contracts ...

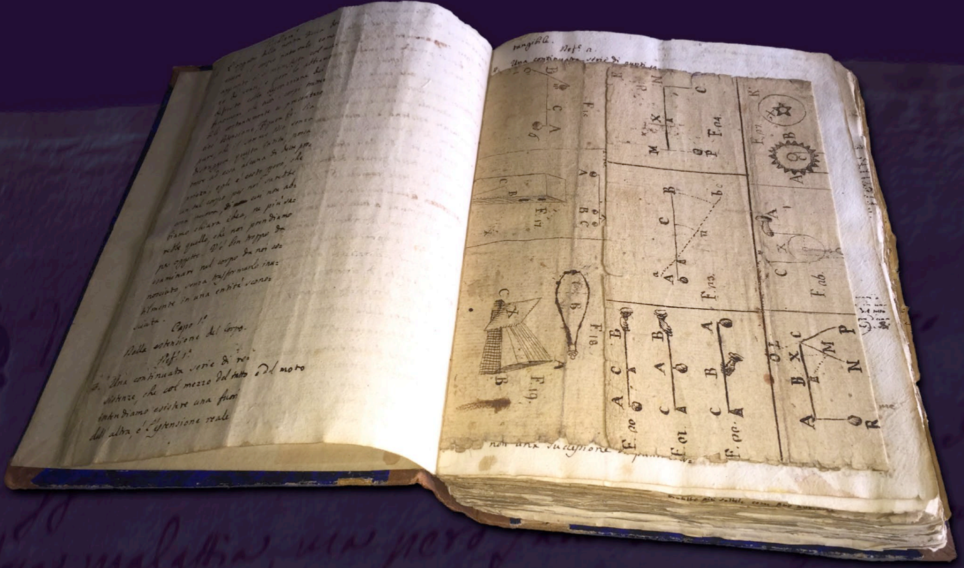
- A variety of formats

  - Single sheets
  - Bounded volumes
  - Closed testaments
  - Scrolls ...

Milestones :

Book

3D Imaging of a
XIX century Physics Book



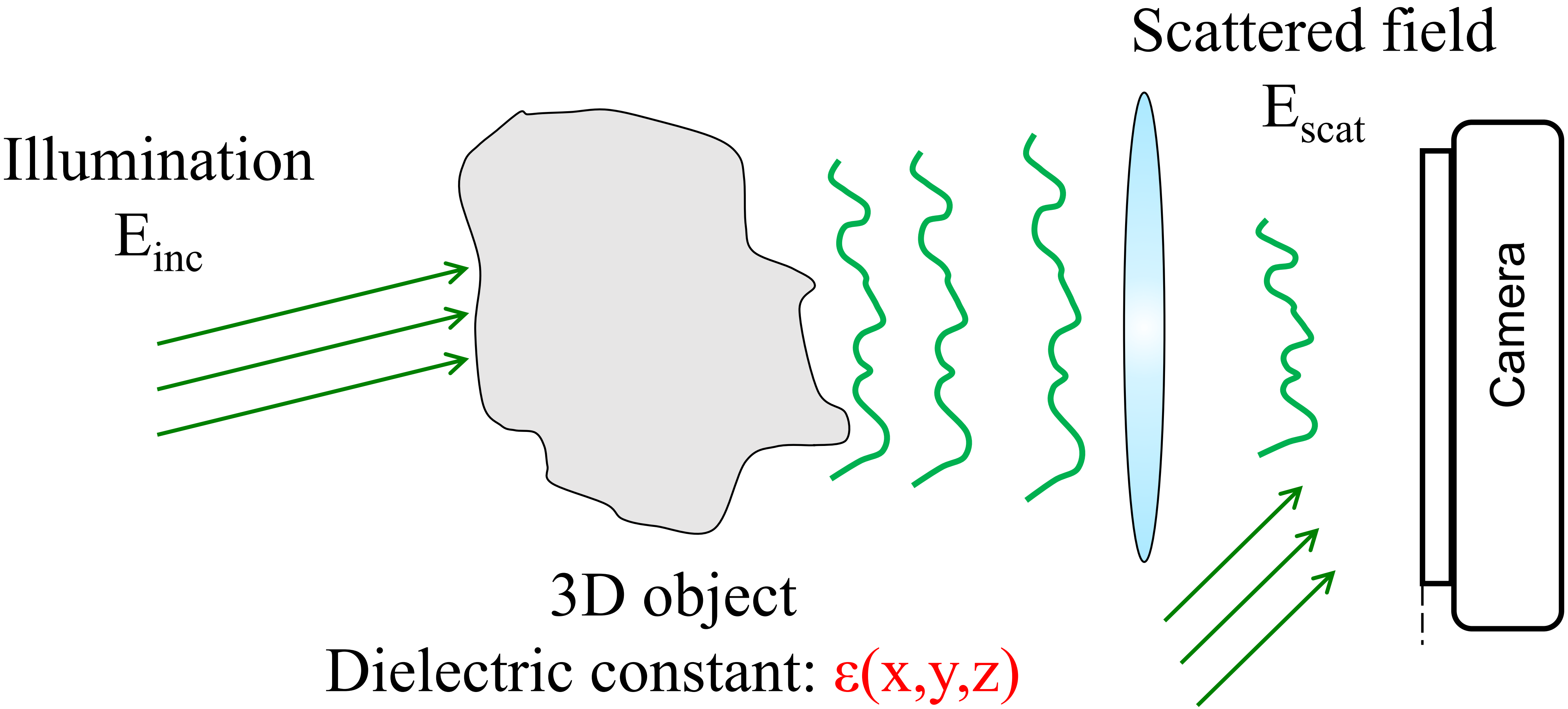
- Handwritten book
  - Text
  - Drawings
- Large size object
  - 20 x 25 cm
  - 200 pages

Milestones :

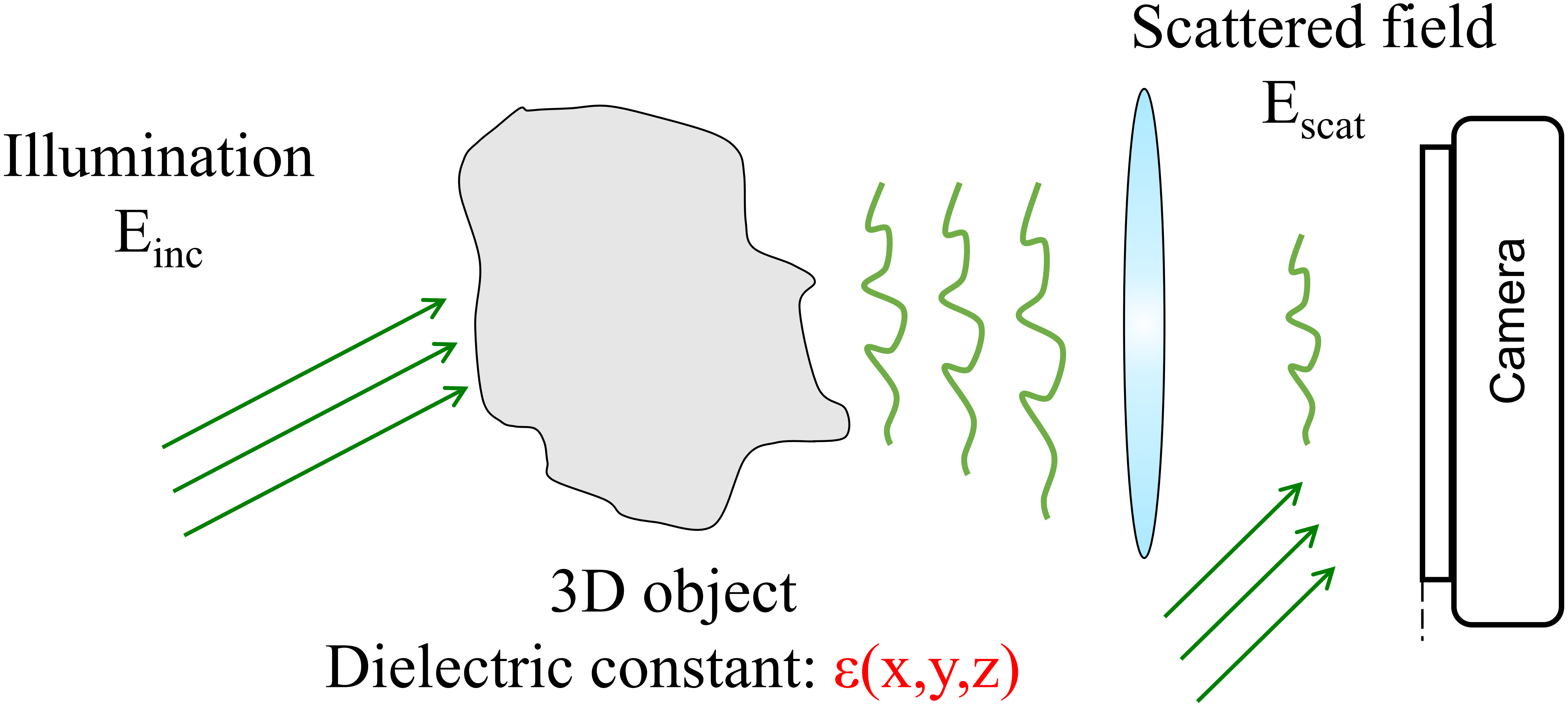
Book

3D Imaging of a
XIX century Physics Book

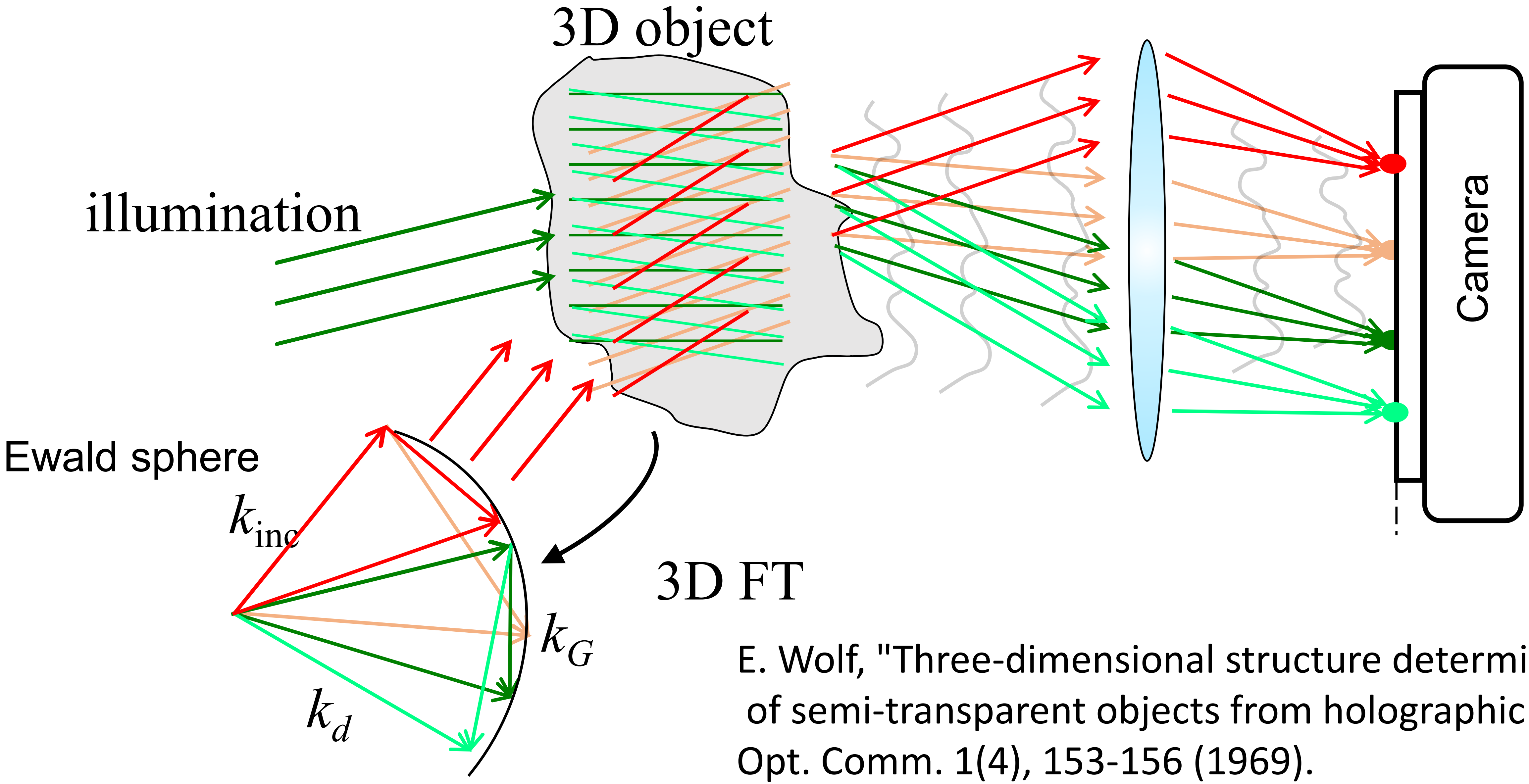
Optical Tomography



Optical Diffraction Tomography

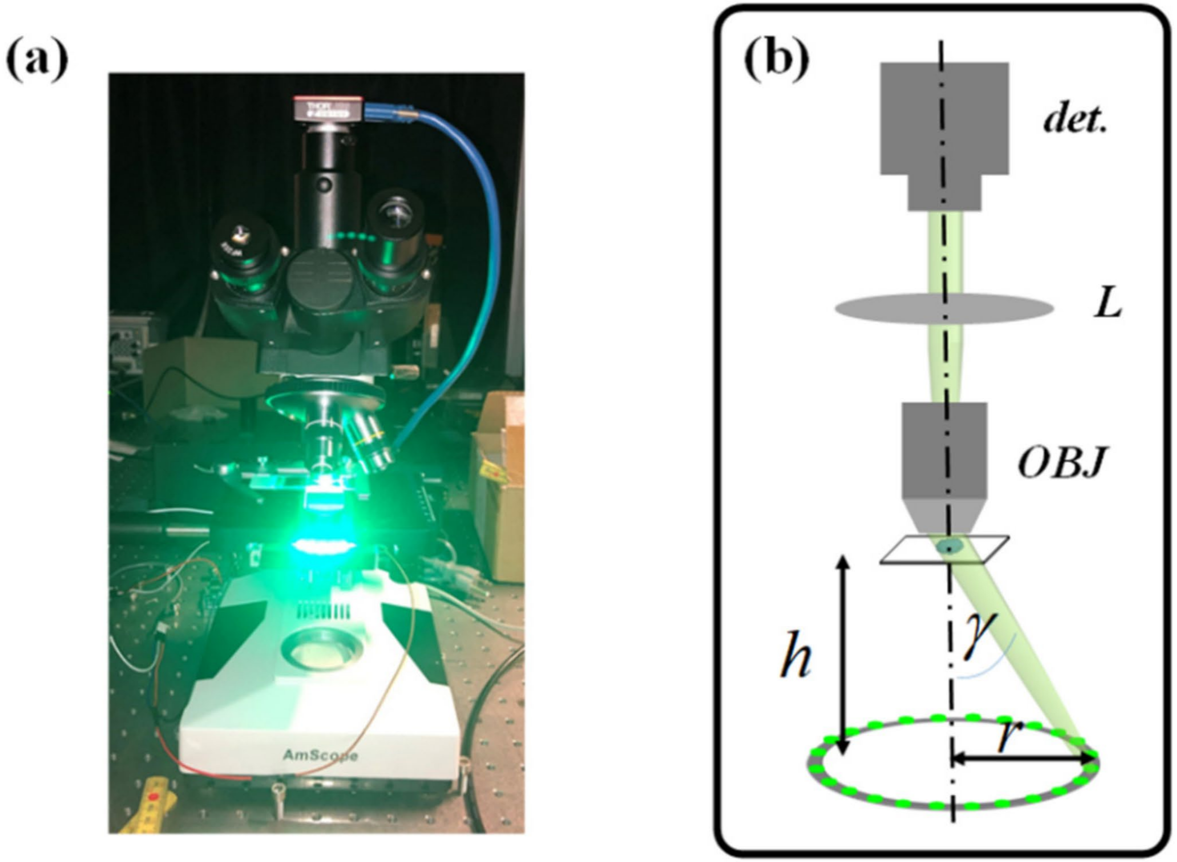


The *Wolf transform*



E. Wolf, "Three-dimensional structure determination of semi-transparent objects from holographic data," Opt. Comm. 1(4), 153-156 (1969).

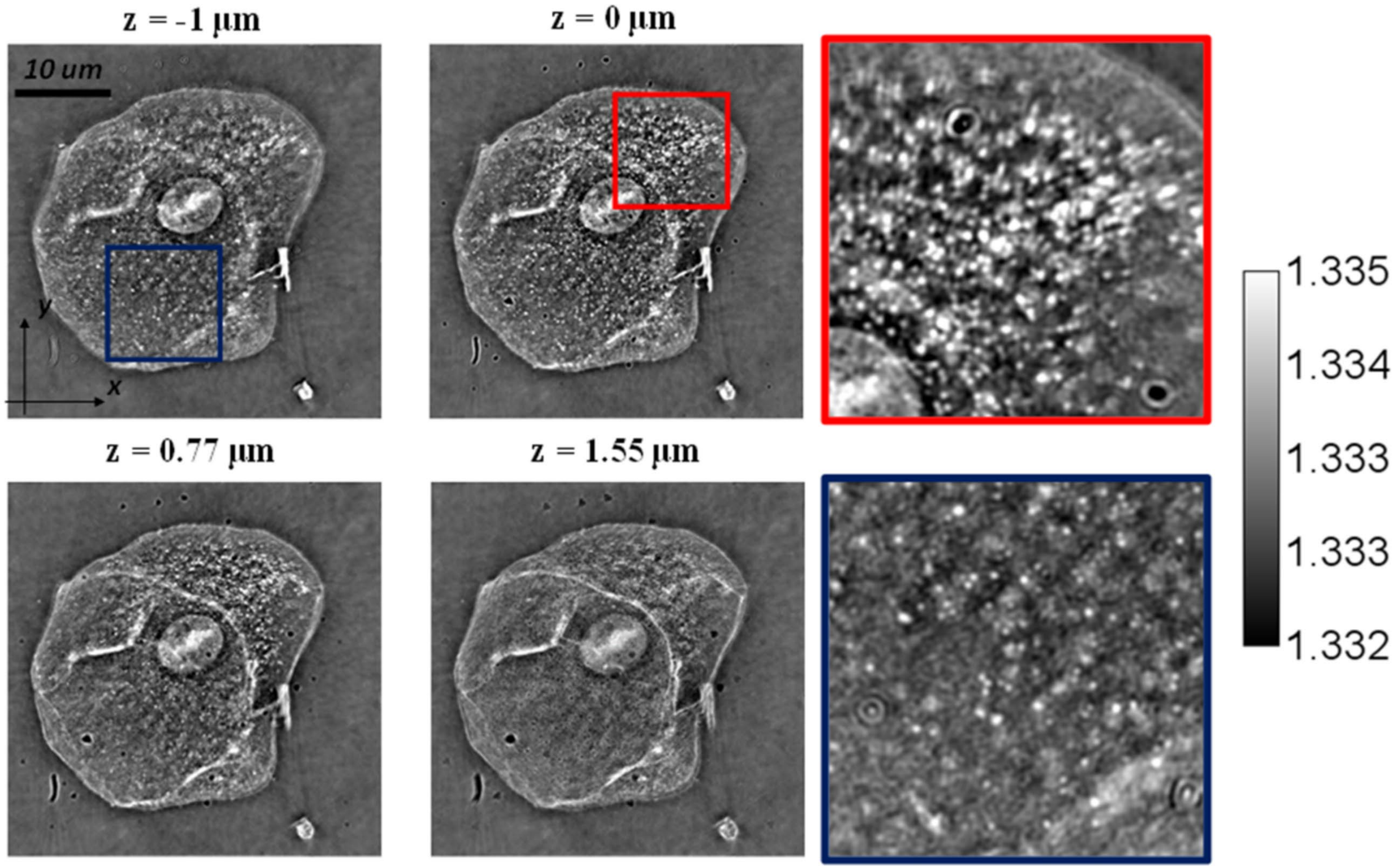
Optical Diffraction Tomography with the LED ring



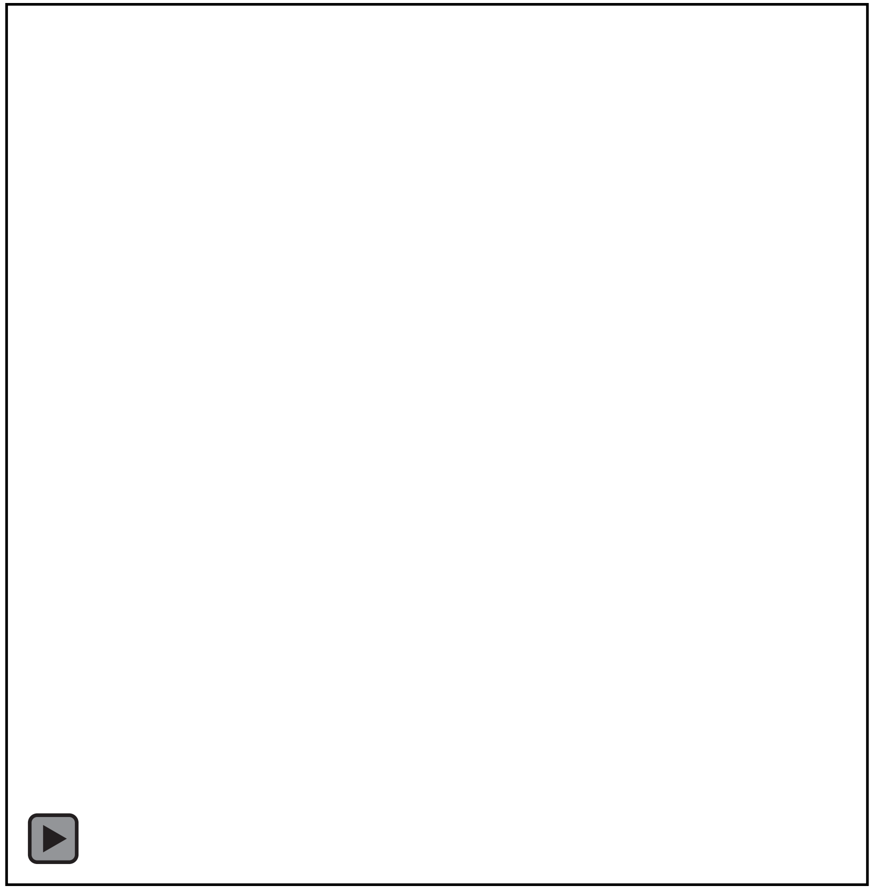
3D intensity and phase imaging from light field measurements in an LED array microscope, Tian and Waller, Optica, 2015
Optical Diffraction Tomography using Nearly In-Line Holography with a Broadband LED Source, Ayoub, Roy and Psaltis, Applied Sciences, 2022.

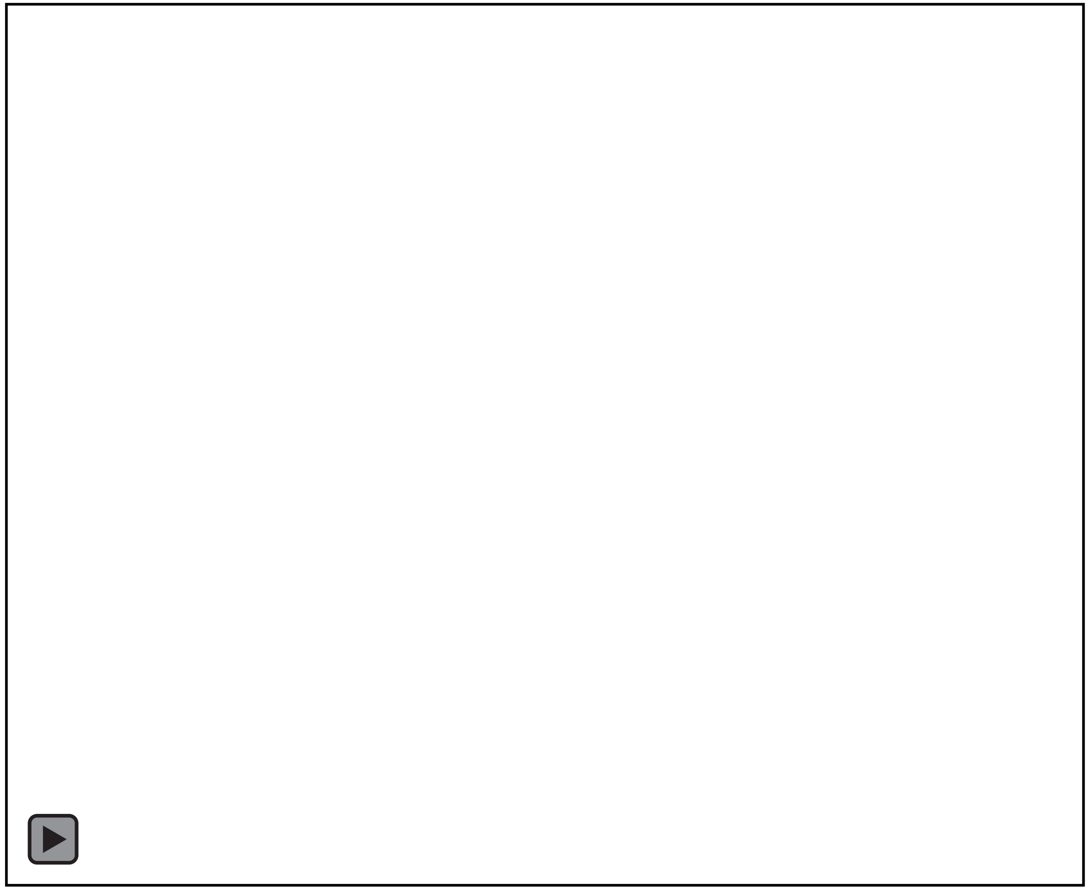
Hologram of cheek cell and its 2D spectrum

Cheek cell reconstruction



3D RI Reconstruction examples

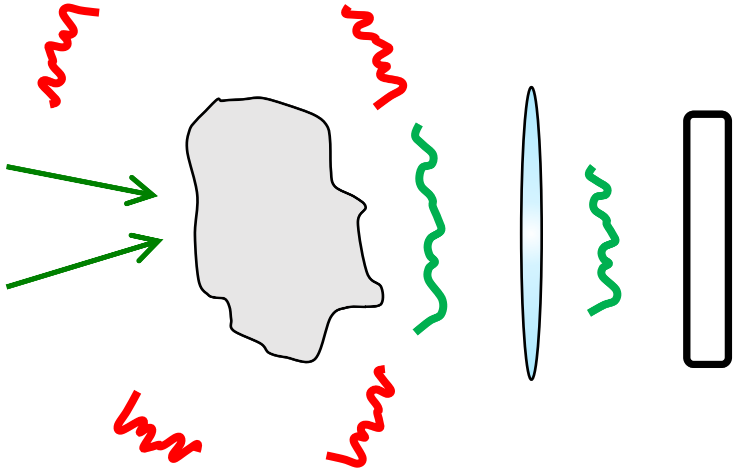




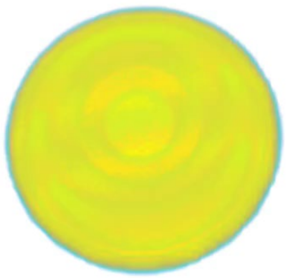
Machine learning for ODT ?

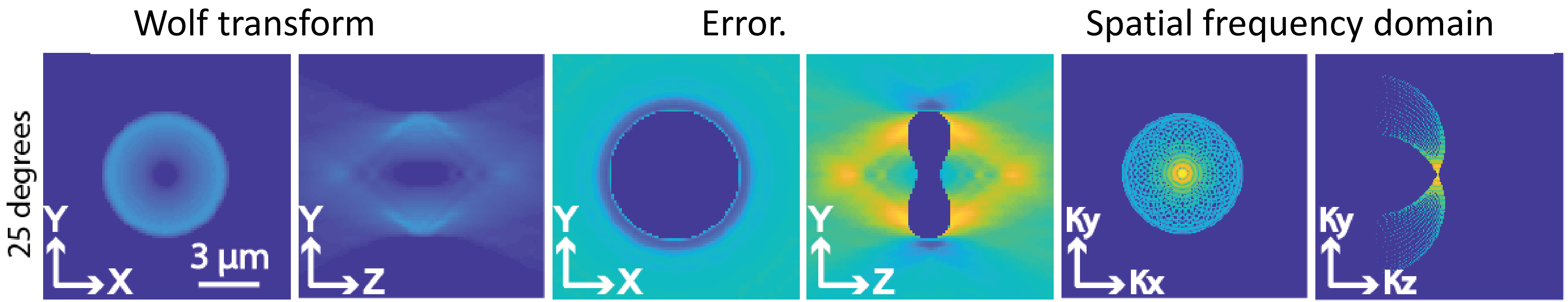
1. Multiple scattering
   (e.g Reflections)
2. Limited Numerical Aperture
   (Missing cone problem)
3. Fast phase from intensity
4. Scalar approximation
   (Birefringent objects)
5. Optical Nonlinearities
6. Denoising
   (Speckle)

The missing cone problem

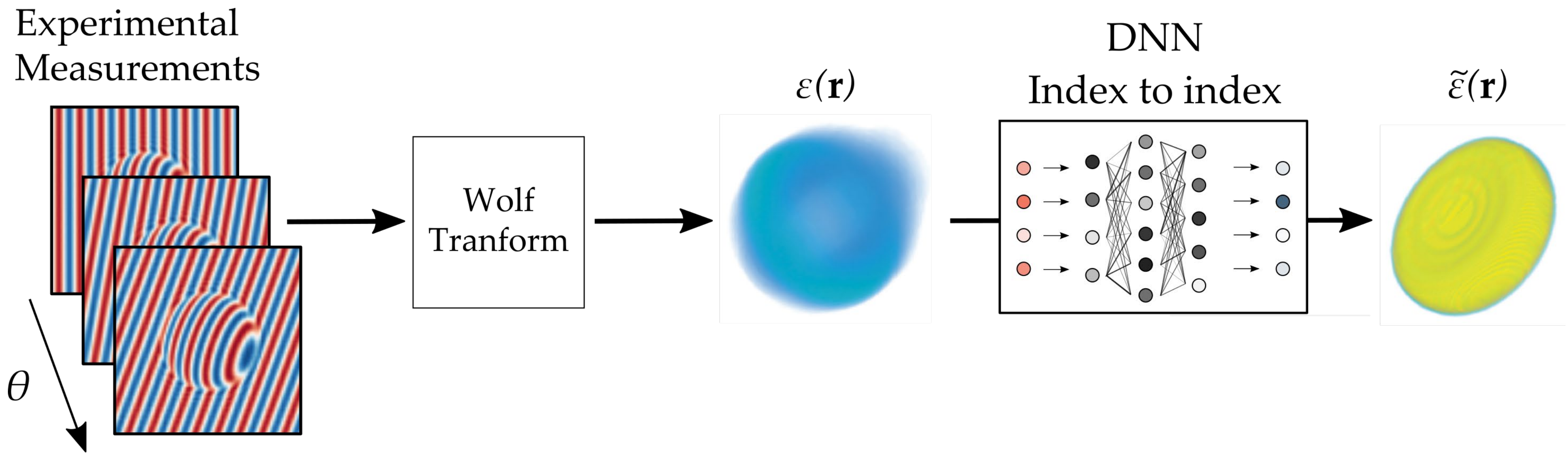


Red blood cell

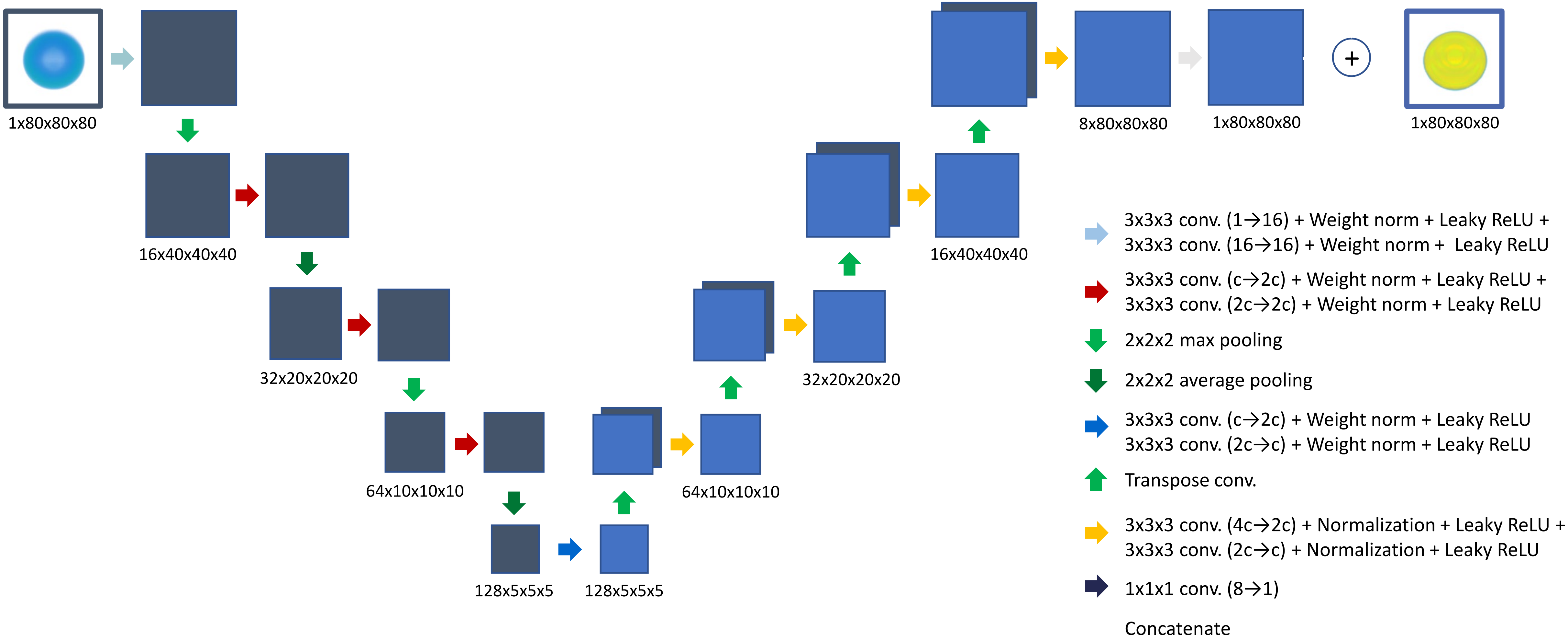




Machine Learning for the missing cone problem

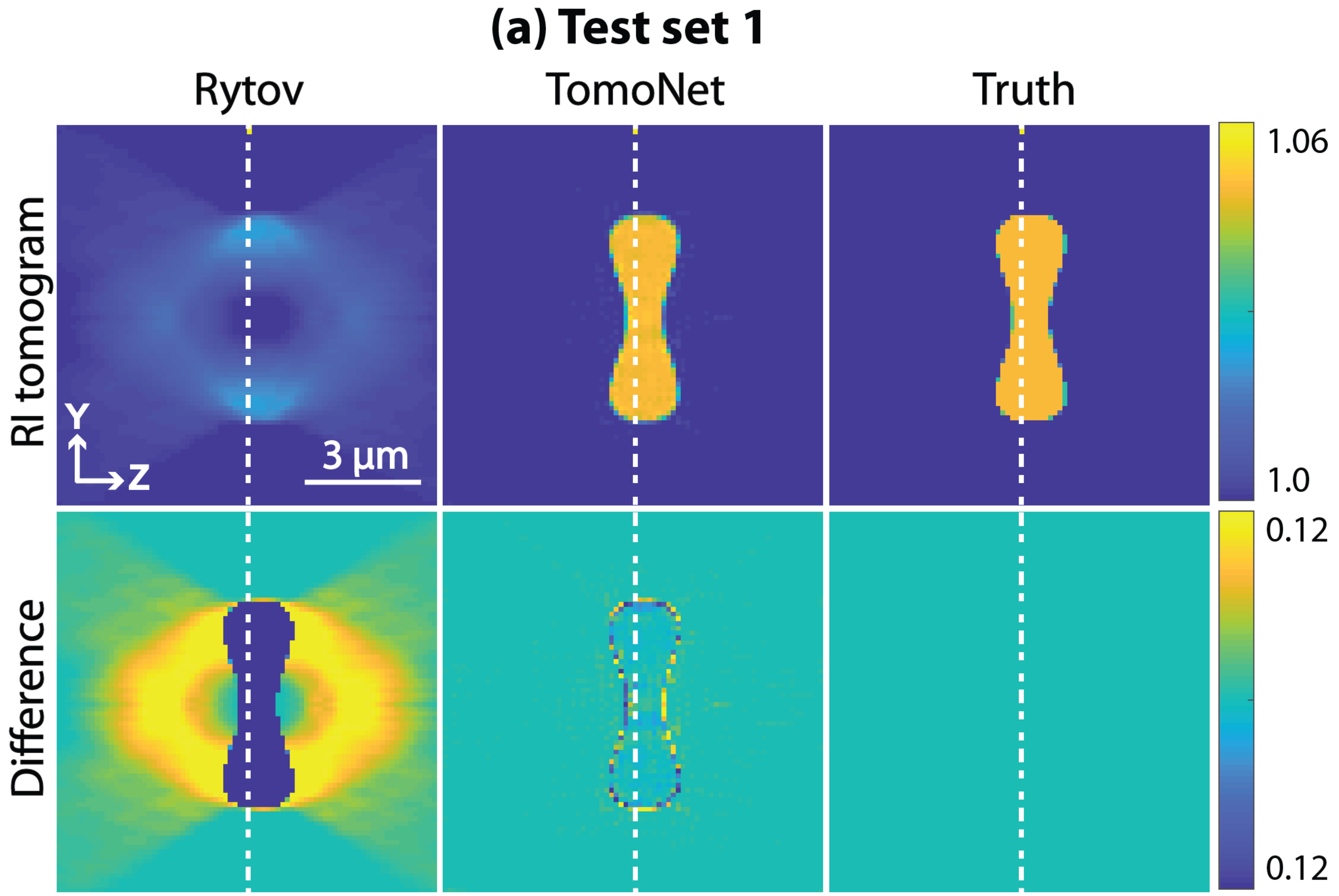


TomoNet structure



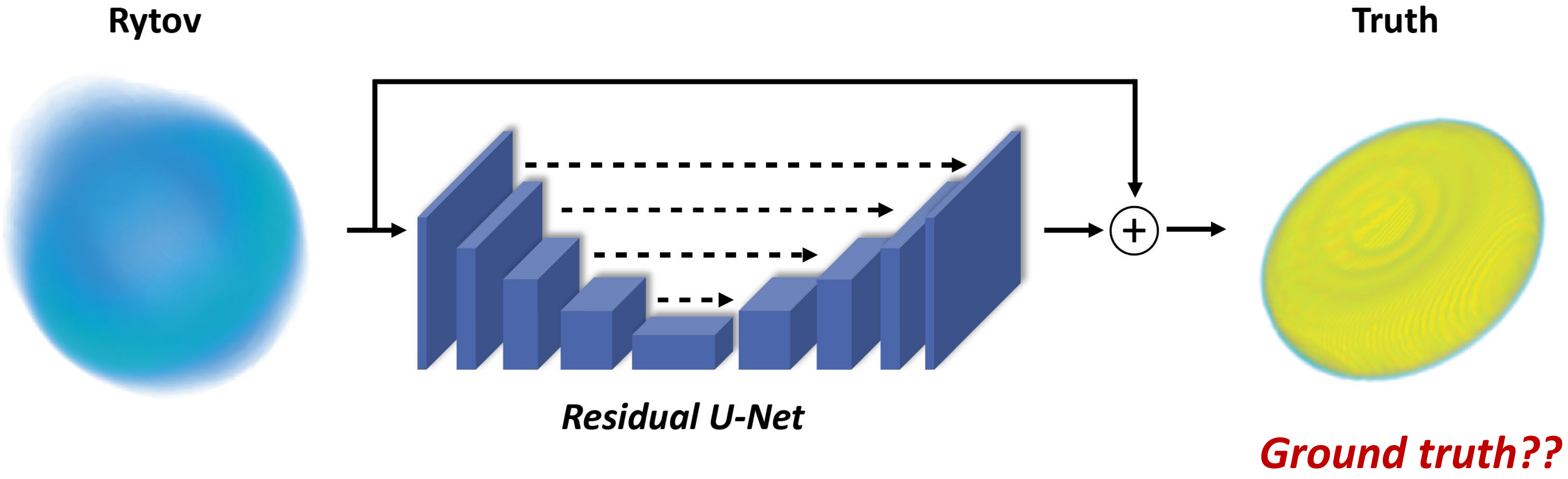
Lim, Joowon, Ahmed B. Ayoub, and Demetri Psaltis. "Three-dimensional tomography of red blood cells using deep learning." Advanced Photonics 2.2 (2020): 026001.

Result on synthetic data



Lim, Joowon, Ahmed B. Ayoub, and Demetri Psaltis. "Three-dimensional tomography of red blood cells using deep learning." Advanced Photonics 2.2 (2020): 026001.

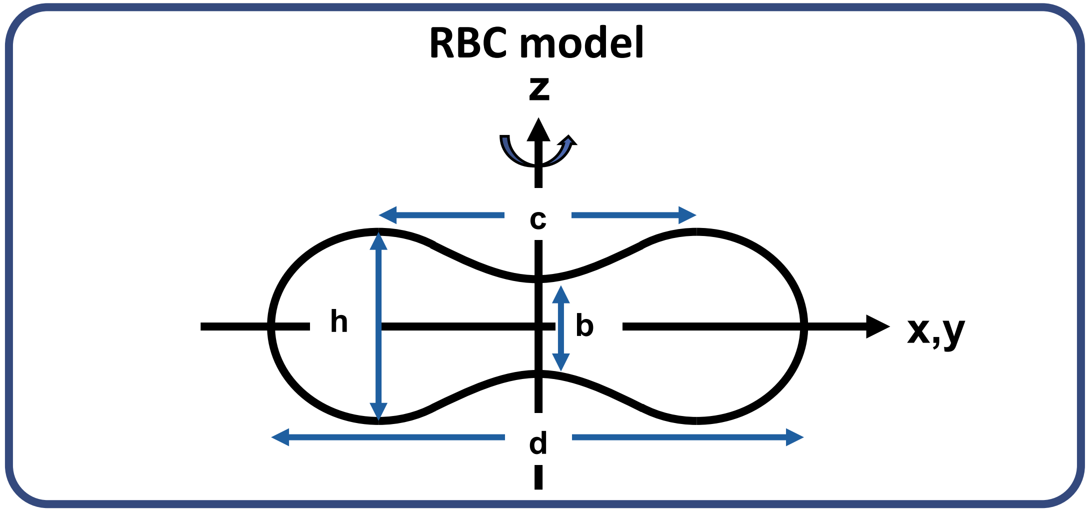
Deep learning based correction for ODT

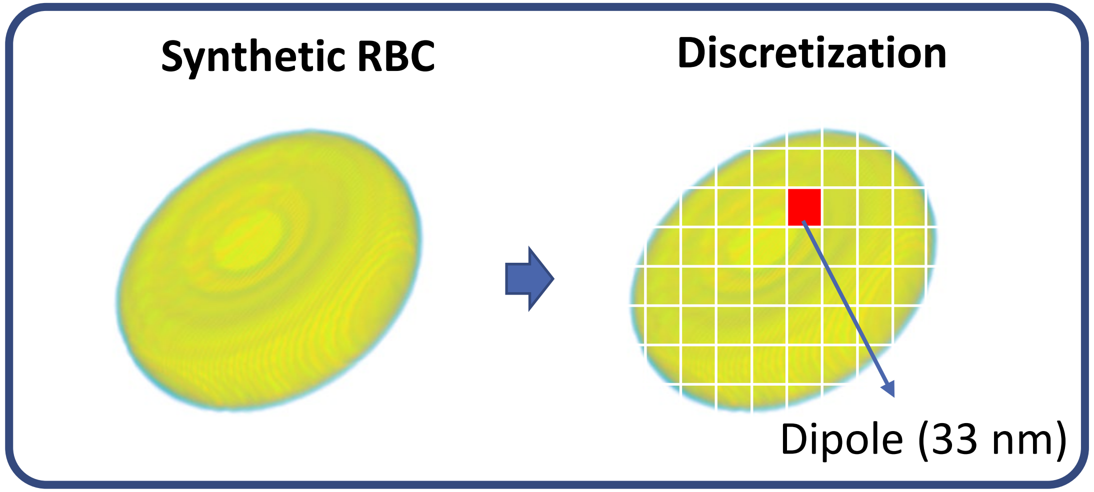


Recent machine learning applications in Optics:

- **Virtual staining :** *Rivenson, Yair, et al., LSA (2019), Borhani, Navid, et al., BOE (2019)*
- **Phase retrieval :** *Borhani, Navid, et al., Optica (2018), Xue, Yujia, et al. Optica (2019)*
- **Classification / Segmentation :** Yoon, Jonghee, et al., Sci. Rep. (2017), Lee, Jimin, et al., IEEE Access (2019)
- **+ Many**

Discrete Dipole Approximation (DDA)





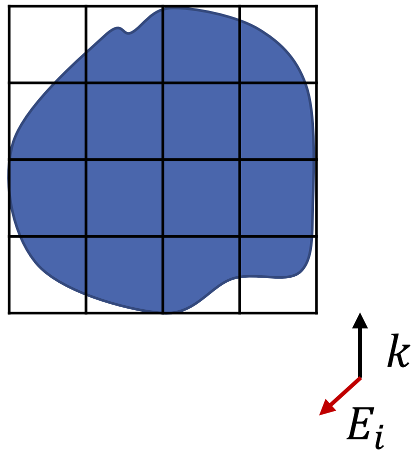
Discrete Dipole Approximation (DDA) [1]

- ✓ For particles of arbitrary geometry
- ✓ Representation of continuum target by discrete dipoles
- ✓ Integral solution of $\nabla^2\boldsymbol{E} + k^2\boldsymbol{E} = 0$

$$\boldsymbol{E}(\boldsymbol{r}) = \boldsymbol{E}^{inc}(\boldsymbol{r}) + \int_{V\setminus V_0} d^3\boldsymbol{r}'\, G(\boldsymbol{r},\boldsymbol{r}')\chi(\boldsymbol{r}')\boldsymbol{E}(\boldsymbol{r}') + \boldsymbol{M}(V_0,\boldsymbol{r}) - \boldsymbol{L}(\partial V_0,\boldsymbol{r})\chi(\boldsymbol{r})\boldsymbol{E}(\boldsymbol{r})$$

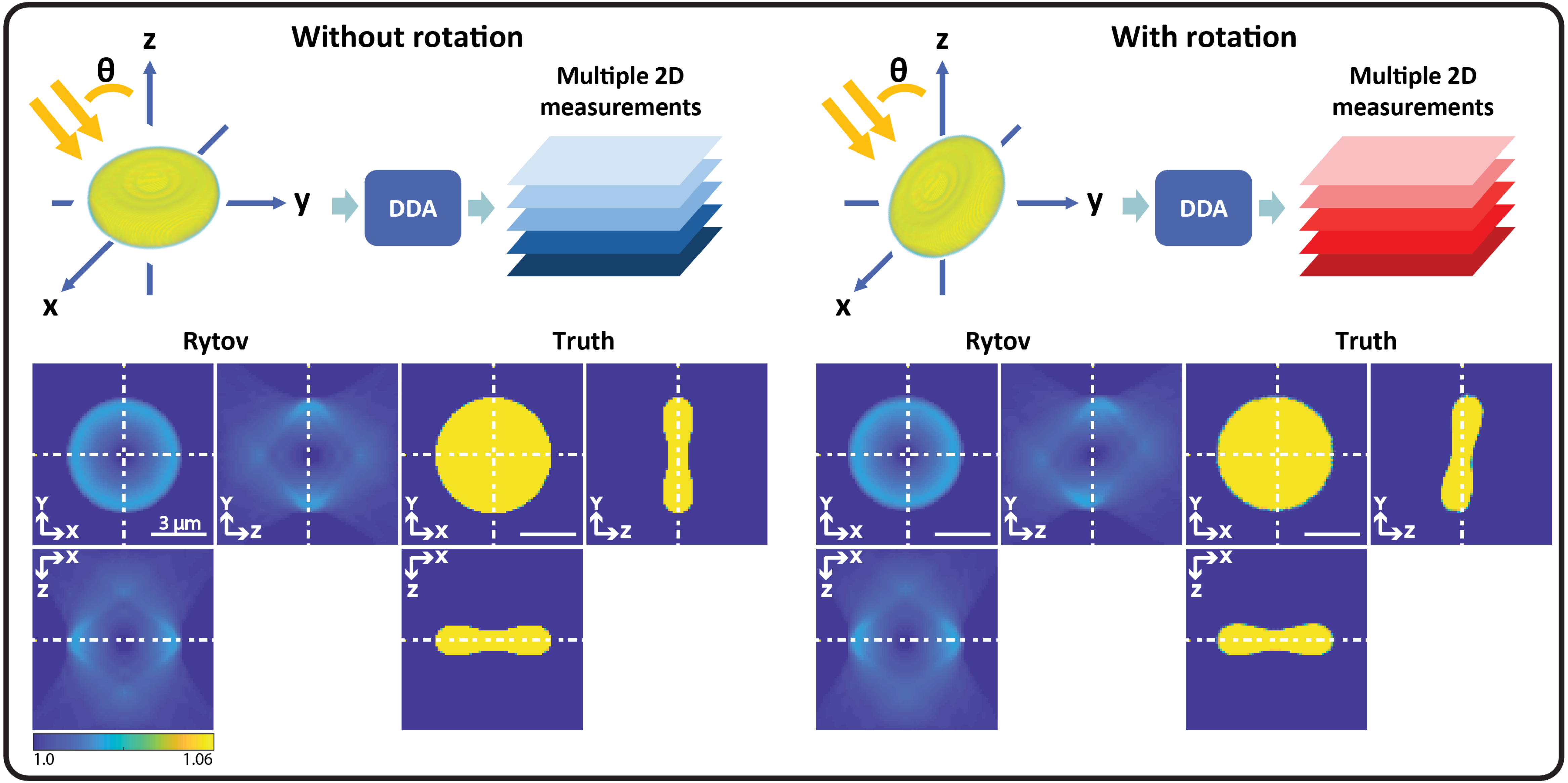
- ✓ Discretization of the solution

$$\boldsymbol{E}(\boldsymbol{r}) = \boldsymbol{E}^{inc}(\boldsymbol{r}) + \sum_{j\neq i}\int_{V_j} d^3\boldsymbol{r}'\, G(\boldsymbol{r},\boldsymbol{r}')\chi(\boldsymbol{r}')\boldsymbol{E}(\boldsymbol{r}') + \boldsymbol{M}(V_i,\boldsymbol{r}) - \boldsymbol{L}(\partial V_i,\boldsymbol{r})\chi(\boldsymbol{r})\boldsymbol{E}(\boldsymbol{r})$$

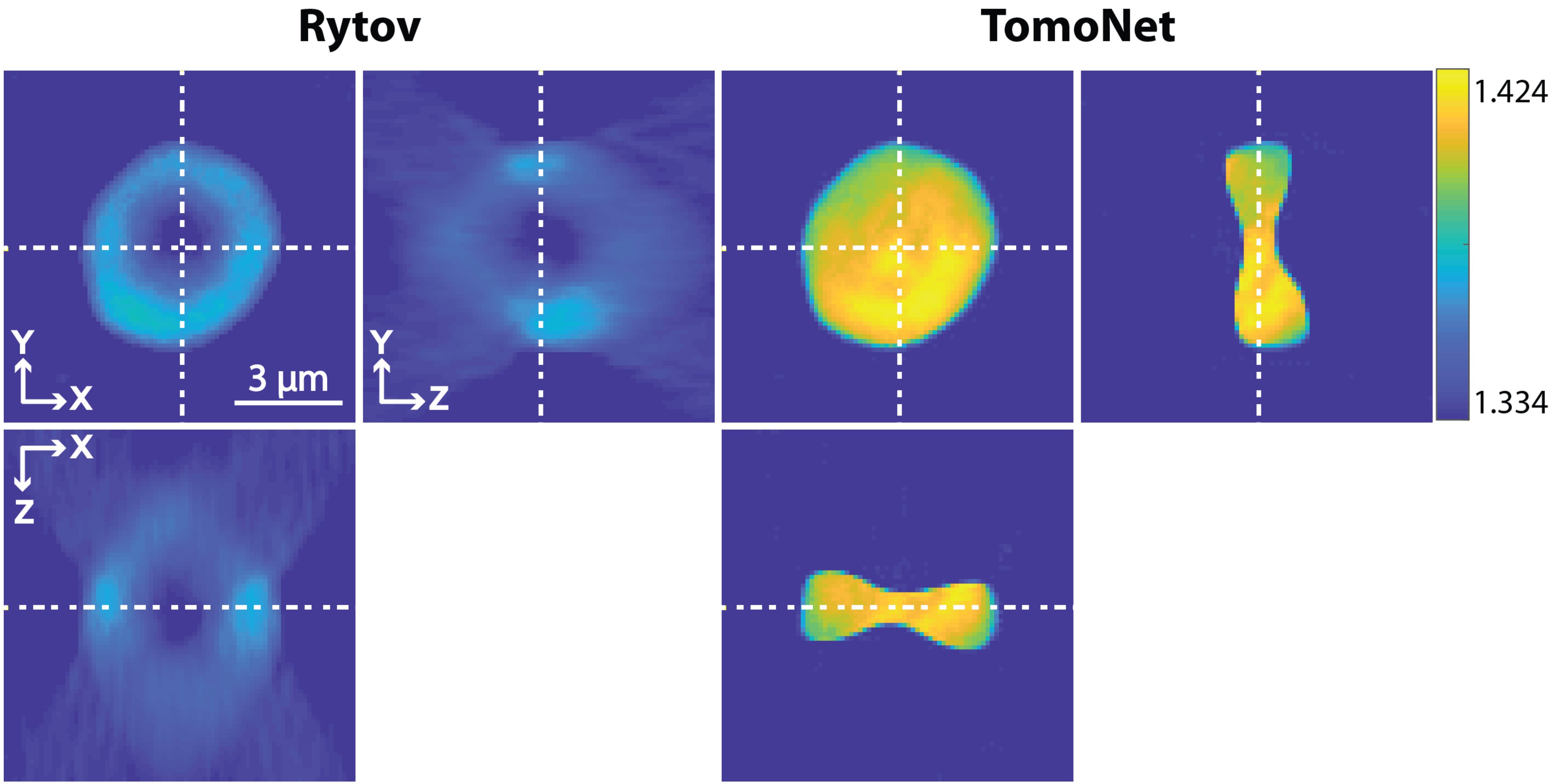


1. Yurkin, Maxim A., and Alfons G. Hoekstra. "The discrete dipole approximation: an overview and recent developments." *Journal of Quantitative Spectroscopy and Radiative Transfer* 106.1-3 (2007): 558-589.

Data generation

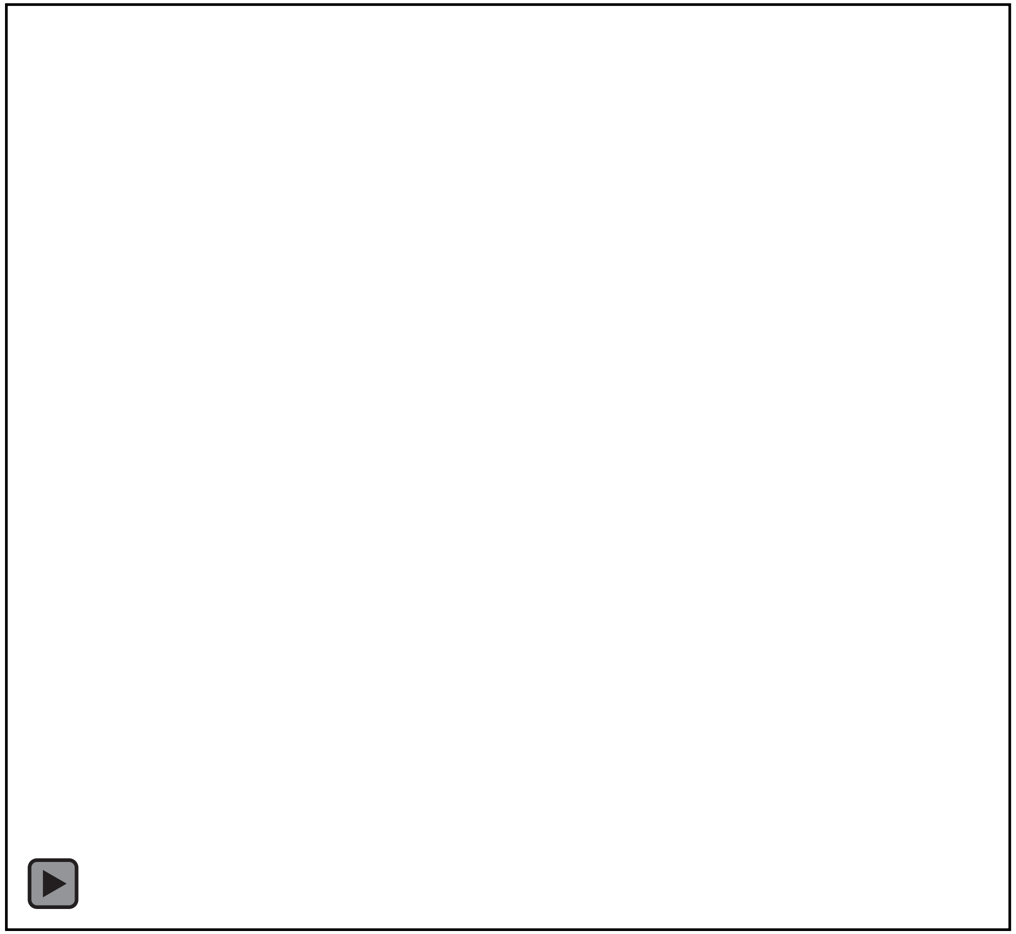


Experimental result

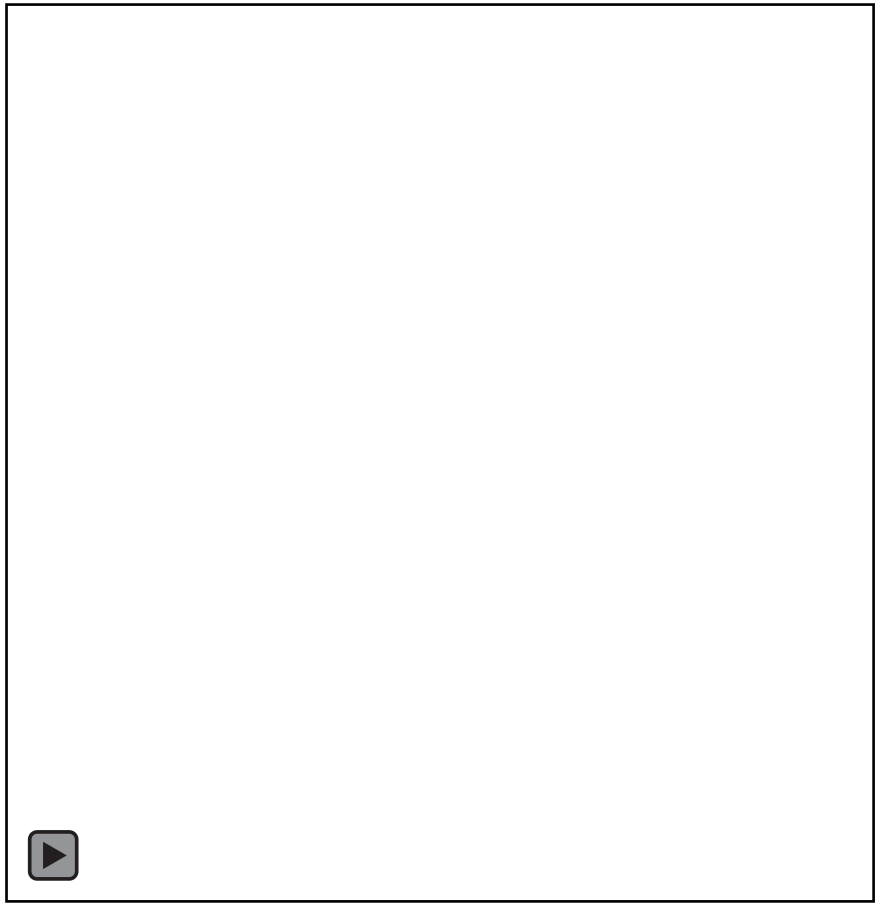


Joowon Lim, Ahmed Ayoub and Demetri Psaltis. "Three-dimensional tomography of red blood cells using deep learning." Advanced Photonics (2020)

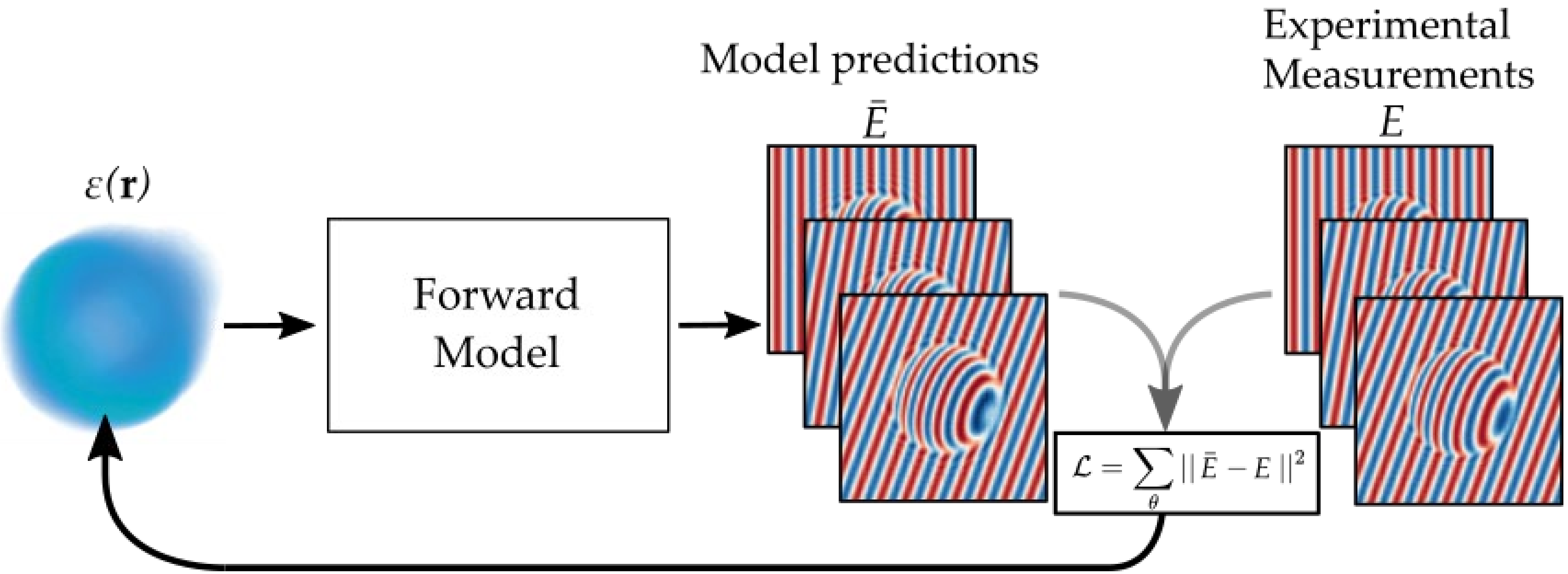
Wolf transform



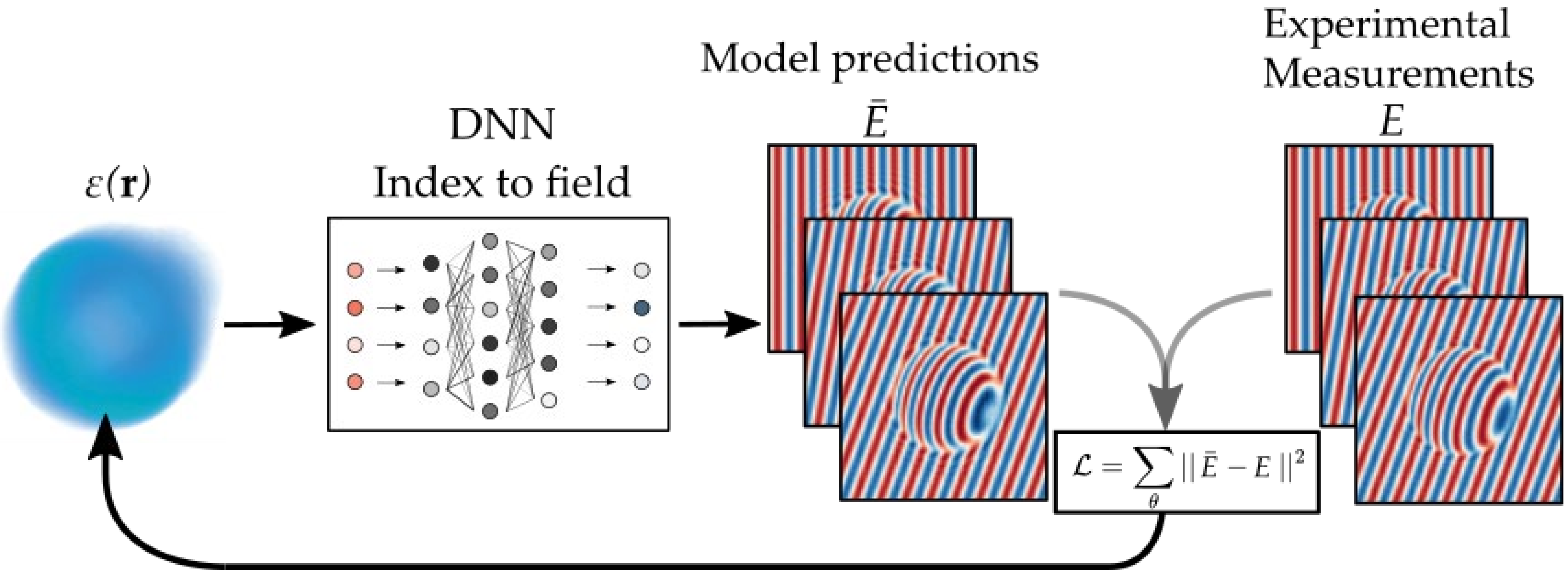
TomoNet



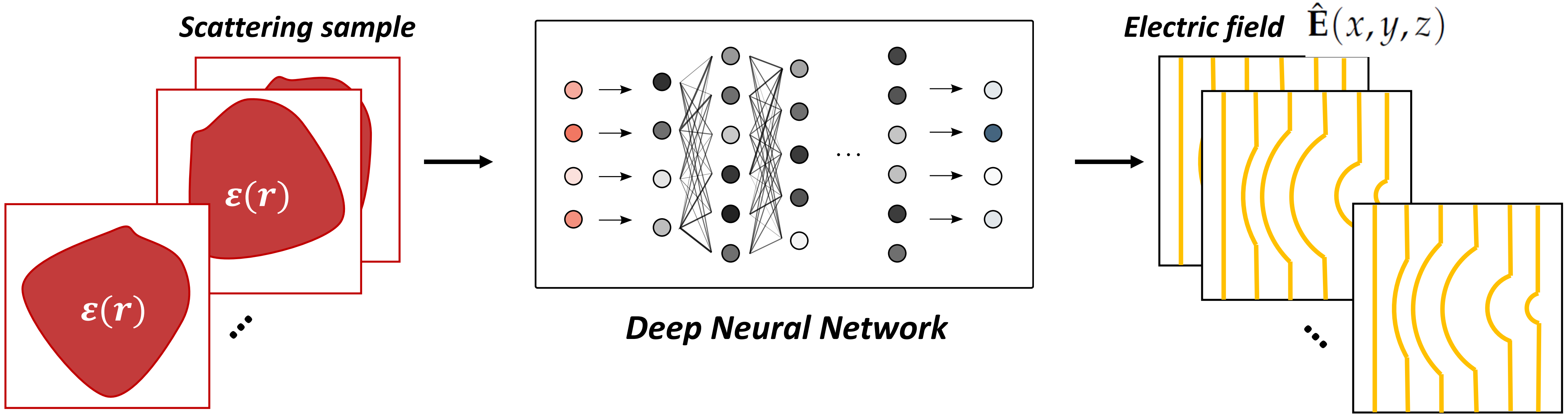
Iterative ODT reconstruction



Neural Network forward Model

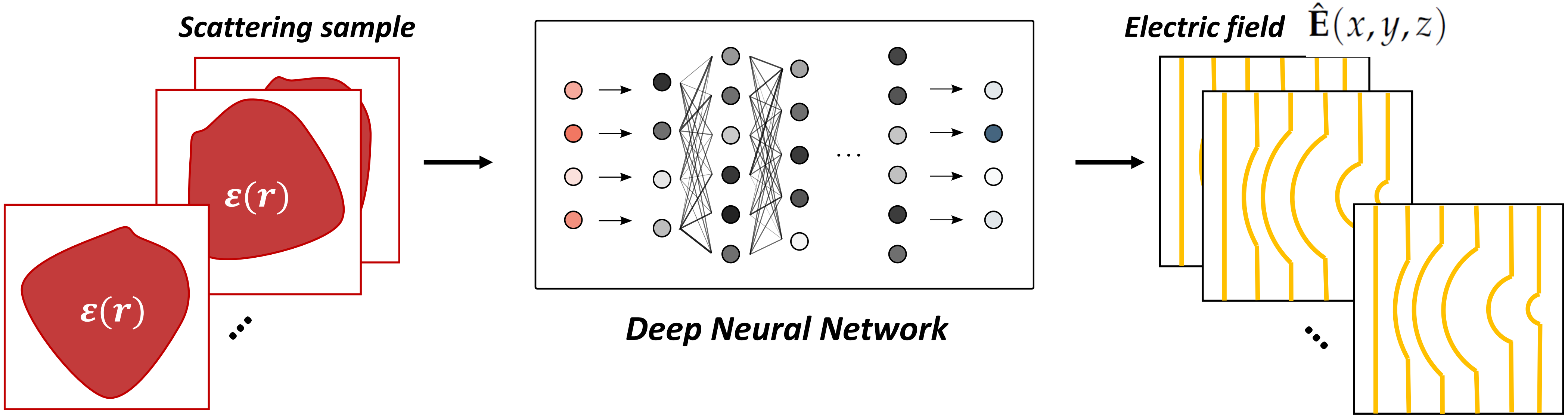


Data-driven neural network



$$\mathcal{L} = \sum_i \left\| \hat{\mathbf{E}}(x_i, y_i, z_i) - \mathbf{E}(x_i, y_i, z_i) \right\|^2$$

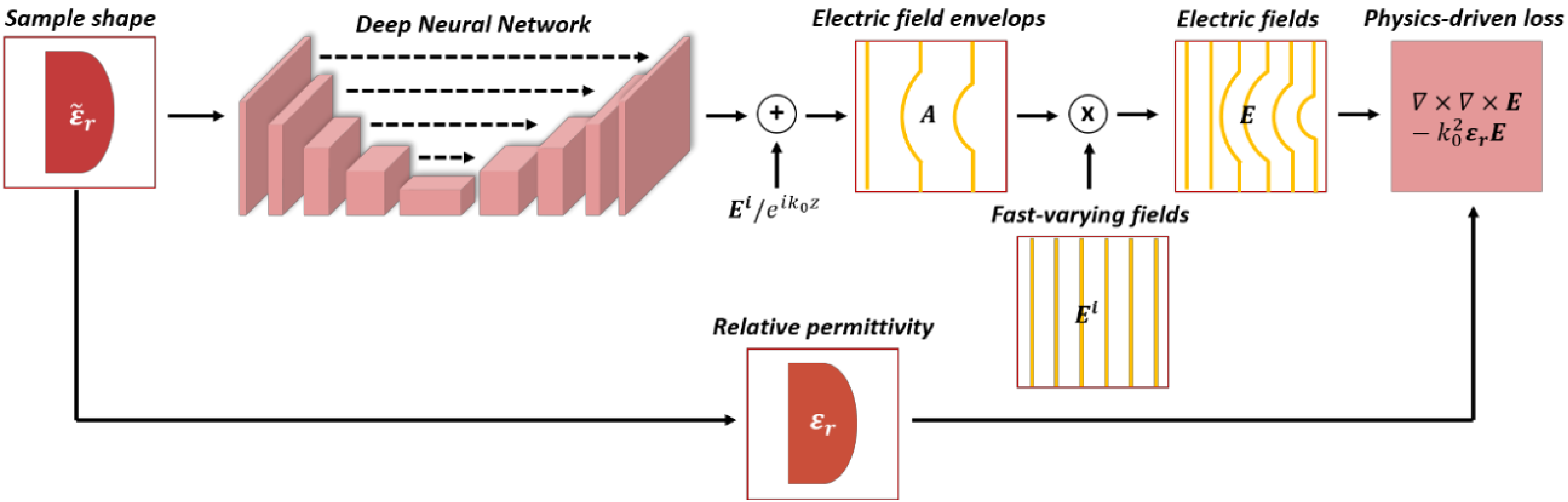
Physics informed neural network



$$\mathcal{L} = \sum_i \left| \nabla \times \nabla \times \hat{\mathbf{E}}(x,y,z) - \frac{\omega^2}{c^2}\varepsilon(x,y,z)\hat{\mathbf{E}}(x,y,z) \right|^2_{x_i,y_i,z_i}$$

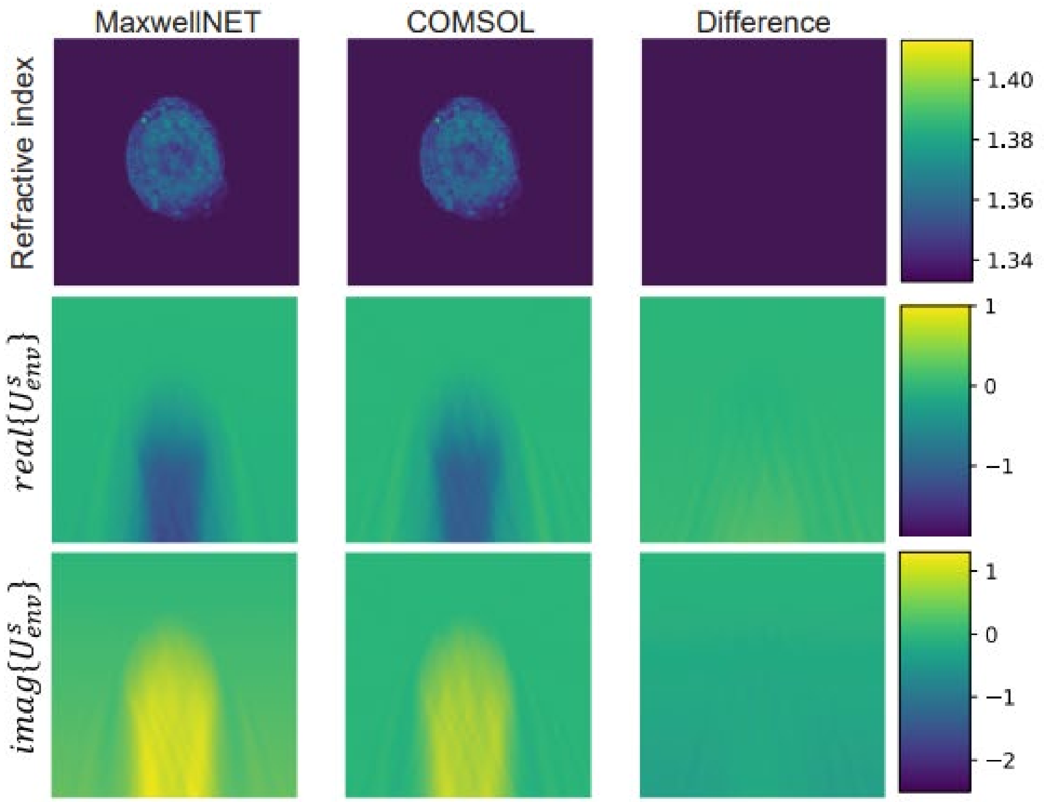
- How to numerically discretize physical loss
- Which is the best network structure to accomplish this task

Maxwell equations based loss function

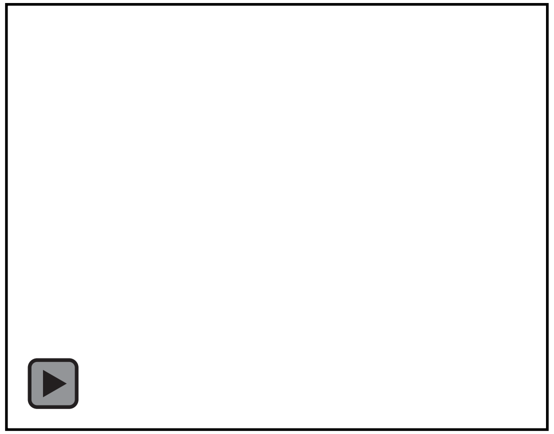


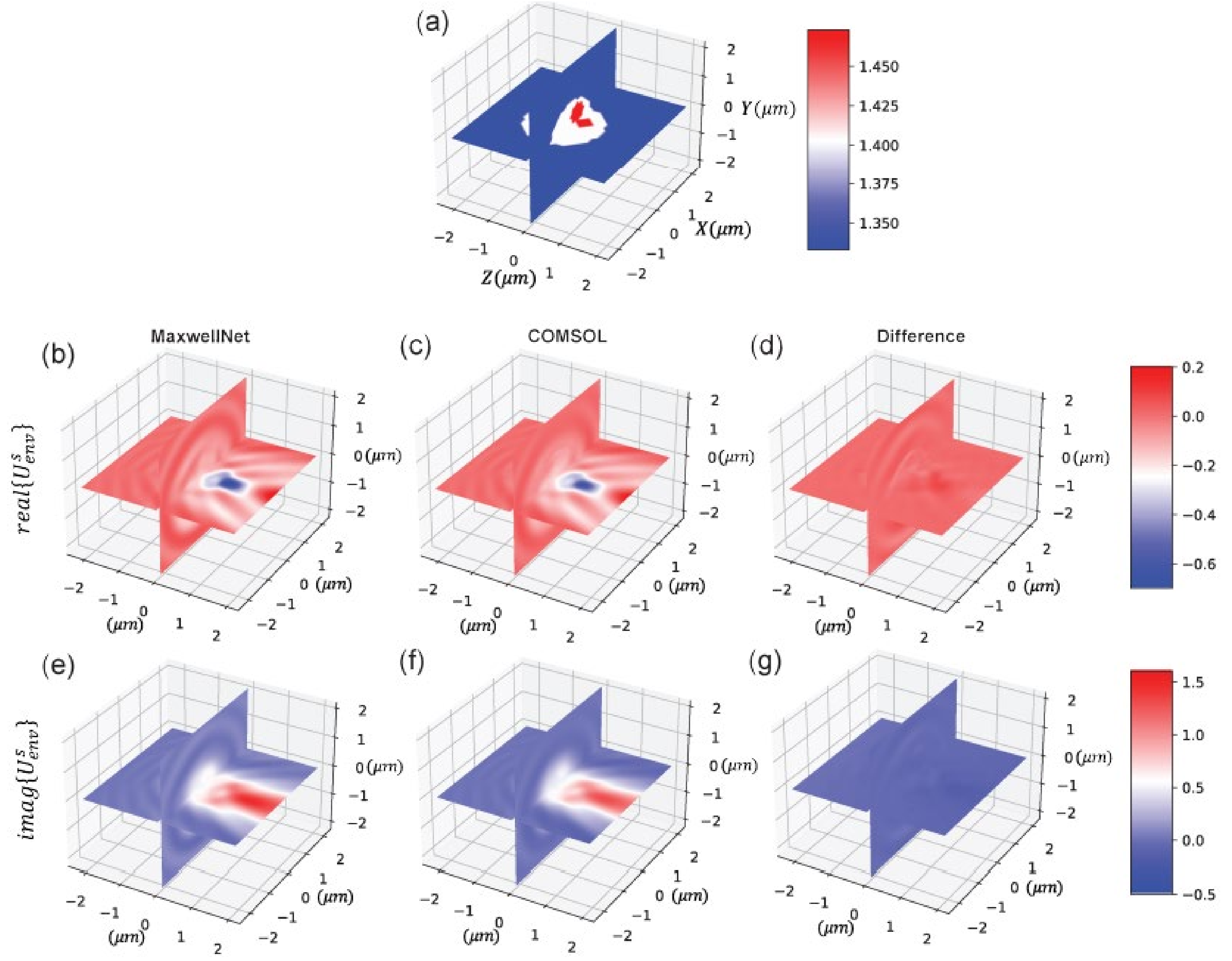
Lim and Psaltis, MaxwellNet: Physics Driven deep neural network based on Maxells equations, APL Photonics, 2022

Results-HCT Cancer Cells



MaxwellNet 3D:

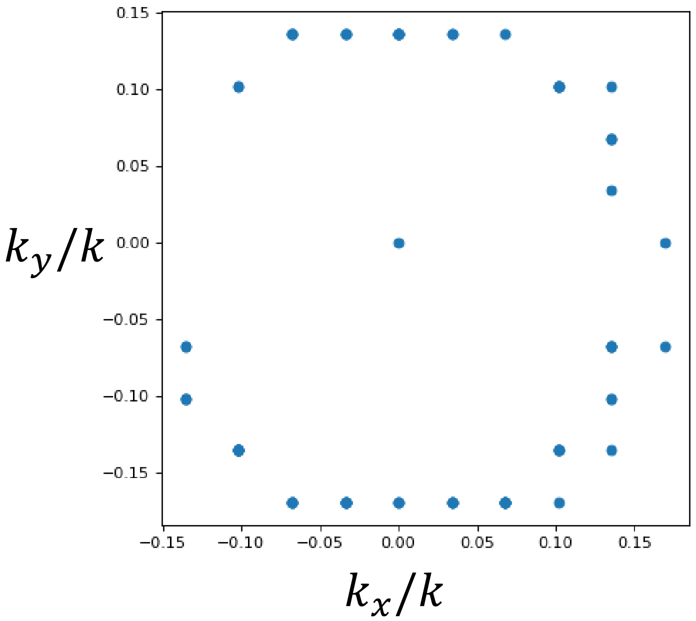


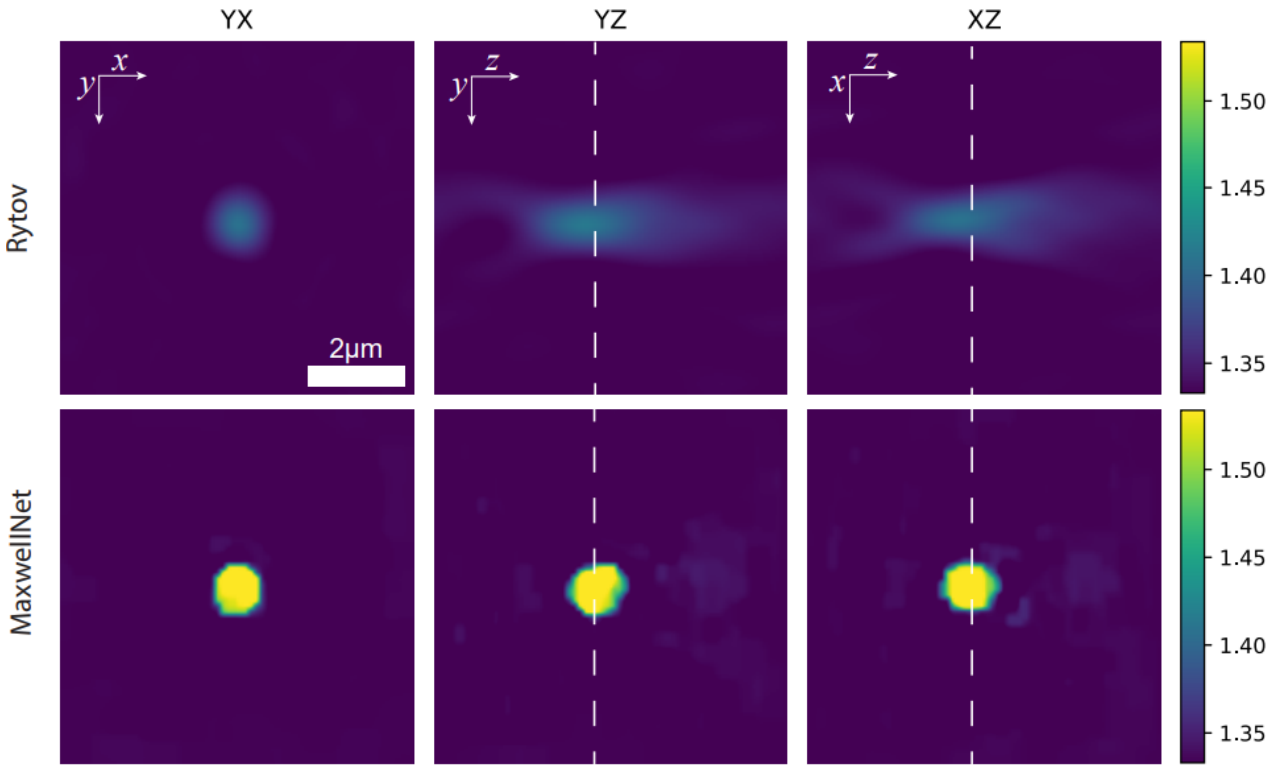


Diffraction Tomography using MaxwellNet

Tomographic Results: **Experiment**

Polystyrene microsphere in water



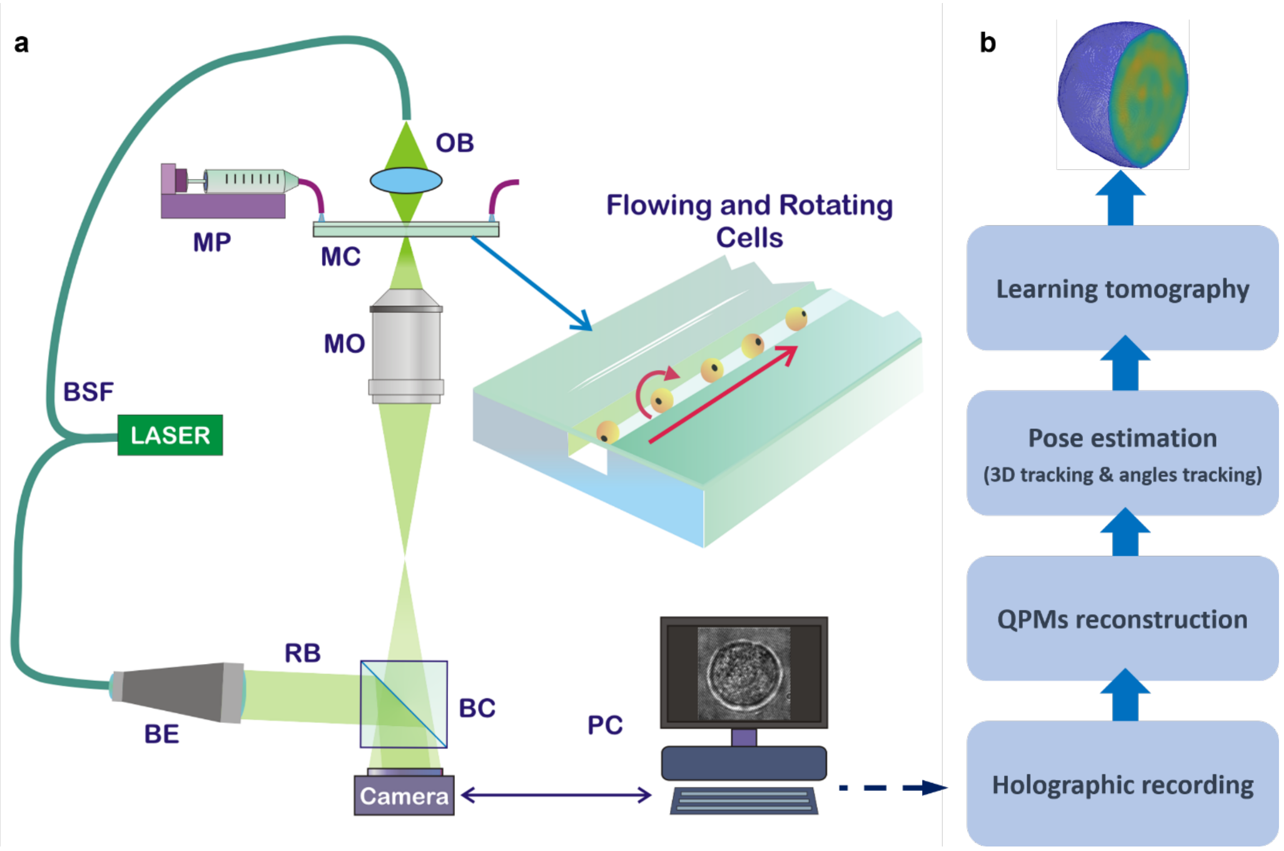


Computation time

Table 1 Computation time comparison

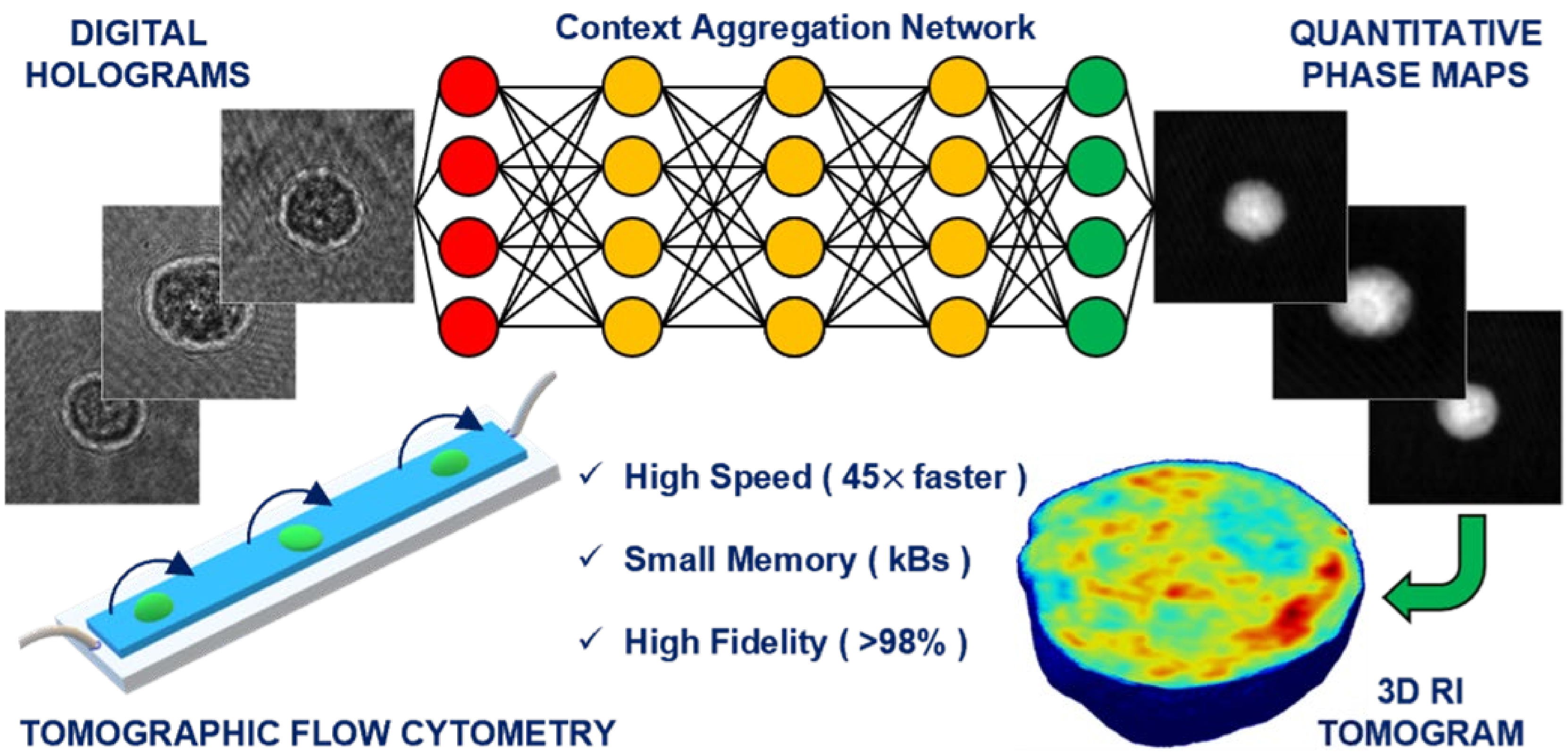
Dataset	2D Phantoms	2D HCT-116	3D Phantoms
MaxwellNET training/fine-tuning	30.5h	0.18h	15.5h
MaxwellNET inference	17.0ms	17.0ms	44.9ms
COMSOL	13s	13s	2472s

TomoFlow



D. Pirone, et.al., Lab on a Chip, 2022.

Deep Learning for TomoFlow

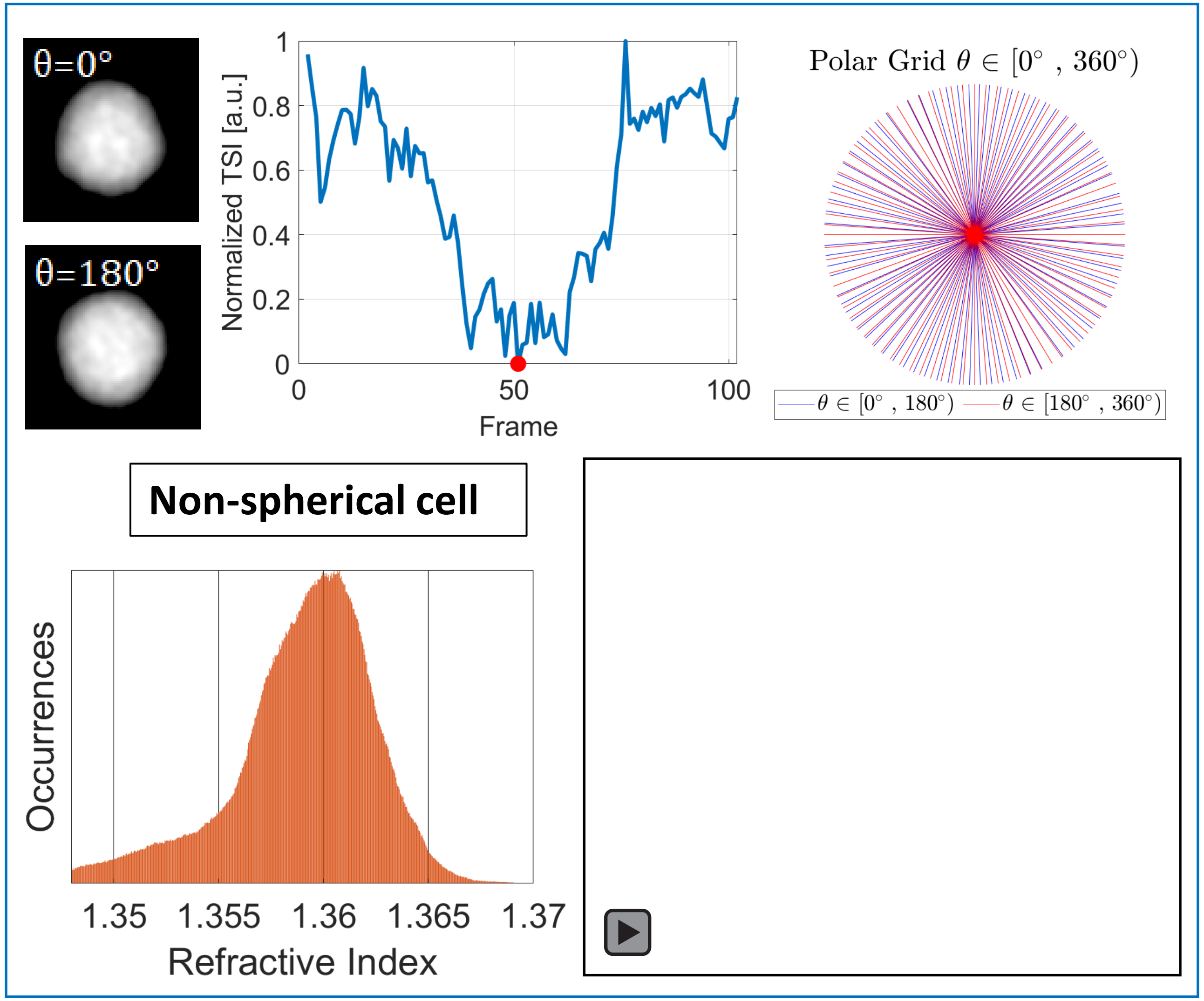


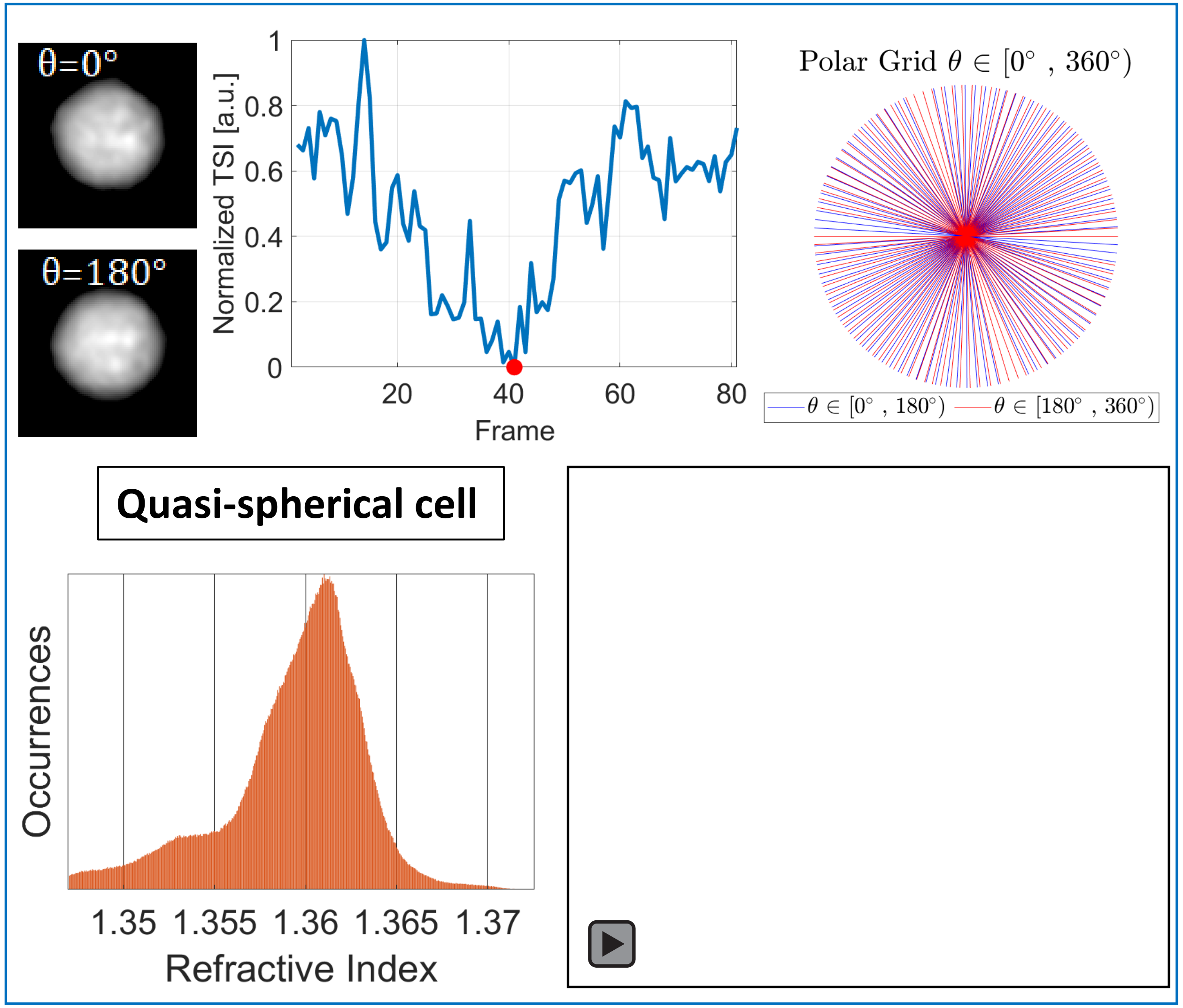
D. Pirone, et.al., Lab on a Chip, 2022.

Nucleus Identification for Breast and Neuroblastoma Cancer Cells

D Pirone, et.al. bioArxiv, 2021

Breast cancer cells by TomoFlow





D. Pirone et al., *Appl Opt* 60(4), A277 (2021).

CTC from breast cancer

Advantages of label-free 3D imaging

- Avoid photobleaching
- Avoid blinking
- Avoid chemical modification
- In vivo imaging
- Flexibility in wavelength selection
- Generally simpler light sources
- etc

Marx, V. It's free imaging — label-free, that is. *Nat Methods* **16,** 1209–1212 (2019)