Overview & Motivation

Wave optics in a nutshell: coherence, Hyugens-Fresnel principle, wave propagation, wave field vs observable intensity, diffraction-limited resolution, …

Goals:

• Intuitive introduction of fundamentals of wave optics without all the math (not enough time, take an optics class for that)
• Overview of modern approaches combining wave optics with artificial intelligence techniques for various applications
Coherence in a Nutshell

- Incoherent light: emission of light over “large” (i.e., compared to wavelength) area & broad range of wavelengths

- Partially coherent light (one of the following):
  - point or plane wave = spatially coherent
  - monochromatic = temporally coherent

- Coherent light: spatially & temporally coherent

Image courtesy: Zeiss

Poisson’s Spot

• Common sense says there’s a shadow behind an occluder, like a disc
• Wave theory predicts bright spot
**Poisson’s Spot**

- **Common sense** says there’s a shadow behind an occluder, like a disc.
- **Wave theory** predicts a bright spot.
- Fresnel predicted, Poisson doubted, and Arago demonstrated it in 1818.
Point Sources and Plane Waves

- Point source at $x_0$ and amplitude $u_0$
  - $r = ||x - x_0||_2, k = \frac{2\pi}{\lambda}$

$$u(x) = u_0 \frac{e^{ikr}}{r}$$

- Propagates with velocity $c$ into direction $k = (k_x, k_y, k_z)$
  - “what comes out of a laser” or collimated point source

$$u(x) = u_0 e^{ik \cdot x}$$

point source

plane wave
Point Sources and Plane Waves

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- Propagates with velocity $c$ into direction $\mathbf{k} = (k_x, k_y, k_z)$
- "what comes out of a laser" or collimated point source
Hyugens-Fresnel Principle

Every point on a wavefront is itself the source of spherical wavelets, and the secondary wavelets emanating from different points mutually interfere. The sum of these spherical wavelets forms the wavefront.

Examples:

- Plane wave through slit → spherical wave
- Plane wave through multiple slits → interfering sph. waves
- Sph. waves make plane wave
- Plane wave through big slit
- Curved wave
Hyugens-Fresnel Principle

Direction: random
Hyugens-Fresnel Principle

Direction: axial
Hyugens-Fresnel Principle

Direction: oblique
Hyugens-Fresnel Principle

Direction: more oblique
Spatial Frequency

<table>
<thead>
<tr>
<th>axial</th>
<th>oblique</th>
<th>more oblique</th>
</tr>
</thead>
<tbody>
<tr>
<td>zero spatial frequency</td>
<td>low spatial frequency</td>
<td>higher spatial frequency</td>
</tr>
</tbody>
</table>

Images/videos from [Zhang & Levoy, 2009]
Interaction of Wave Field and Thin Object

- Field before/after object $u_{in/out}(x)$ are defined by amplitude $a(x)$ and phase $\phi(x)$ of mask (or object) as

$$u_{out}(x) = u_{mask}(x) u_{in}(x) = a(x)e^{i\phi(x)} u_{in}(x)$$

- **slit**
  - $a(x) = \delta(x - x_0)$
  - $\phi(x) = 1$

- **amplitude mask**
  - $a(x) = \text{rand}$
  - $\phi(x) = 1$

- **lens**
  - $a(x) = 1$
  - $\phi(x) = -\frac{k}{2f}x^2$

- **phase mask**
  - $a(x) = 1$, $\phi(x) = \text{rand}$
Plane Wave Decomposition = Fourier Transform

- Every wavefield can be represented as a weighted sum of plane waves

\[ u(x) = \int \hat{u}(k_x) e^{2\pi i k x} dk_x \]

1D plane wave with slope
Optical Fourier Transform via Wave Propagation

Propagating plane waves in free space is intuitive \(\rightarrow\) long distances in free space or lenses perform optical Fourier transform

Far Field

Long distance compared to wavelength

Lens

Long distance compared to wavelength
Wave Propagation in Free Space

Free-space propagation by distance $z$ is modeled by convolution with a complex-valued propagation kernel or, similarly, a multiplication with a transfer function $\mathcal{H}$ in the Fourier domain.

$$u_{\text{prop}}(x, y) = \mathcal{F}^{-1}\{\mathcal{F}\{u(x', y')\} \cdot \mathcal{H}(k_x, k_y, z)\}$$

$$\mathcal{H}(k_x, k_y, z) = \begin{cases} e^{-i \frac{2\pi}{\lambda} \sqrt{1 - (\lambda k_x)^2 - (\lambda k_y)^2} z} & \text{if } \sqrt{k_x^2 + k_y^2} < \frac{1}{\lambda} \\ 0 & \text{otherwise} \end{cases}$$

Different propagation operators have different transfer functions, this one is called Angular Spectrum Method (ASM).
Complex Field vs. Observable Intensity

We cannot directly observe the field, only its squared amplitude or intensity.

\[ I(x, y) = |u(x, y)|^2 = |a(x, y)e^{i\phi(x, y)}|^2 = a^2(x, y) \]

observable intensity \quad \quad amplitude squared, no phase information!

complex-valued field
Constructive & Destructive Interference

\[ |a_1 e^{i\phi_1} + a_2 e^{i\phi_2}|^2 = a_1^2 + a_2^2 + 2a_1 a_2 \cos(\phi_1 + \phi_2) \]
Diffraction-limited Resolution

1D:  
- Aperture is $\text{rect}(ru)$
- Wave at sensor is $\text{sinc}(krx)$
- Intensity is $|\text{sinc}(krx)|^2$, $k = \frac{2\pi}{\lambda}$

2D:  
- Aperture is $\text{circ}(r)$
- Wave at sensor is $jinc(kr \sin \theta) = \frac{J_1(kr \sin \theta)}{kr \sin \theta}$
- Intensity is $|jinc(kr \sin \theta)|^2$

Airy disk

First minimum at radius $\frac{\lambda}{1.22 \frac{\lambda}{2n \sin \theta}}$

$n \sin \theta$ related to f-number or NA of lens
Diffraction-limited Resolution

Can resolve 2 points if distance $d$ is at least:

- Rayleigh Limit $1.22 \frac{\lambda}{2n \sin \theta}$
- Abbe Limit $\frac{\lambda}{2n \sin \theta}$

$n$ is refractive index of medium.
4f system

- 4f system consists of 2 lenses spaced at 2x their focal length f
- Image plane is copied at 4f distance
- Fourier plane between lenses
Optical Correlator

- Amplitude or phase mask placed at Fourier plane performs optical filtering / correlation
- Can implement low-, high-, or bandpass filter optically!

[Lugt, 1964]
Optical CNN

- Copy input image & convolve with different kernels = CNN

[Diagram of optical CNN setup with labeled parts: input plane (DMD), lens, Fourier plane (phase mask), lens, output plane (camera sensor)]
Optical Computing

Deep Diffractive Neural Networks

Photonic Integrated Circuit

[Lin et al., 2018] [Shen et al., 2017]
AI and Related Optical Implementations

- **1950**
  - AI
    - Book: *The Organization of Behavior*
      - Wetzstein et al., 2020
    - The perceptron
      - Rosenblatt, 1957

- **1960**
  - Adaptive switching circuits
    - Widrow & Hoff, 1960

- **1970**
  - The Hopfield network
    - Hopfield, 1982
  - Multi-layer perceptron with backpropagation
    - Rumelhart et al., 1986

- **1980**
  - Self-organized feature maps
    - Kohonen, 1982
  - Digit recognition with CNNs
    - LeCun et al., 1990

- **1990**
  - Deep autoencoder
    - Hinton & Salakhutdinov, 2006

- **2000**
  - Deep CNNs
    - Krizhevsky et al., 2012

- **2010**
  - Optical AI
    - Optical correlation
      - Lugi, 1964
    - Paper: “Optical interconnections for VLSI systems”
      - Goodman et al., 1984
    - Paper: “Optical implementation of the Hopfield model”
      - Farhat et al., 1985
    - ONN with nonlinear photoreactive crystals
      - Psaltis et al., 1990
    - Deep learning with nanophotonic circuits
      - Shen et al., 2017
    - Neuromorphic photonic networks
      - Tait et al., 2017
    - High-bandwidth photonic neurosynaptic network
      - Feldman et al., 2019
    - Optical CNN
      - Chang et al., 2018
    - All-optical diffractive neural networks
      - Lin et al., 2018

[Wetzstein et al., 2020]
Deep Optics

End-to-end Optimization of Optics and Image Processing
Jointly optimize optics and image processing end-to-end!
Deep Optics

Training:
end-to-end in simulation

Loss
Deep Optics

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

Inference:
- Fabricate lens or other physical components, run network
Case Study:

Image Classification in Low Light


A classification task

BM3D $\rightarrow$ Inception-v4 Classification

Low-Light Mobile Imaging Scenario
Learning Image Processing

Differentiable pipeline $\xrightarrow{}$ optimize end-to-end

Optics Design & Optimization
Low-level Image Processing, i.e. ISP
High-level Image Processing, i.e. CNN
Unrolling Image Optimization

Low-Level Vision

• Physical image formation
• Prior and hyperparameters free
• Differentiable

High-Level Vision
High-Level Vision

Low-Level Vision

- Bad Pixel Correction
- Black Level
- Demosaic
- Denoise
- Lens Correction
- Metering
- Image Enhancing
- Tone Mapping

Unrolling Image Optimization
Unrolling Image Optimization

Unrolled Network

Low-Level Vision

High-Level Vision

Output Layer

Hidden Layer

Input Layer

$h_{t+1}$ $h_{t}$ $h_{t-1}$ $h_{t+2}$ $x_{t+1}$ $x_{t}$ $x_{t-1}$ $x_{t+2}$
Low-Light Classification

Pretrained Inception-v4

BM3D → Pretrained Inception-v4

Proposed joint architecture

Toilet Seat

Spotlight

Espresso

Maracas

Croquet Balls

Balloons

3 lux

PSNR 12.34 dB

PSNR 22.81 dB

PSNR 20.77 dB

6 lux

PSNR 16.39 dB

PSNR 20.71 dB

PSNR 17.97 dB
Case Study:
Monocular Depth Estimation


Pipeline

Ikoma et al., ICCP 2021
Prototype

Ikoma et al., ICCP 2021
Results

- Estimate RGB image and depth map from a single optically coded image
Case Study:

3D Localization Microscopy

Fluorescence Microscopy
PSF of a widefield microscope

Focal plane  Objective lens  Fourier plane  Tube lens  Sensor
PSF engineering - Double Helix PSF

Focal plane  Objective lens  Fourier plane  Tube lens  Sensor

Phase modulation

(Pavani et al. 2009)
Other PSFs for Single Molecule Localization

- Astigmatism
  - 750 nm
  - (Shechtman et al. 2014)

- Double helix
  - 750 nm
  - (Pavani et al. 2009)

- Biplane
  - 750 nm
  - (Juette et al. 2008)

- Saddle-point
  - 750 nm
  - (Shechtman et al. 2014)

- Tetrapod (3µm)
  - -1500 nm
  - (Shechtman et al. 2015)

- Tetrapod (5µm)
  - -2500 nm
Deep Learning–based PSF Engineering

Multi-path imaging system

Target Volume

Optical Encoder

Sensor Model

Electronic Decoder

Estimated Super-resolved Volume

Phase Masks

Sensor

Objective

Tube lens

Sample

Fourier plane

Sensors

Ikoma et al
Optimized Two-shot 3D PSFs

Captured

Simulation

Ikoma et al.
Preliminary Results

Fixed cells with beads

Time lapse of live cells

Ikoma et al.
Case Study:

Hybrid Optical-Electronic Computing

Learning Optics & CNN

Optics Design & Optimization

Low-level Image Processing, i.e. ISP

High-level Image Processing, i.e. CNN

differentiable pipeline → optimize end-to-end
Hybrid Optical-Electronic CNNs

Phase-coded Aperture

4f system

input plane (DMD)  lens  Fourier plane (phase mask)  lens  output plane (camera sensor)

Chang et al., Scientific Reports 2018
Hybrid Optical-Electronic CNNs

**current results:**
- 2x classification accuracy for same power
- half power for same classification accuracy

Chang et al., Scientific Reports 2018
Case Study:

Neural Sensors


Other Examples

HDR Imaging
Metzler et al. CVPR 2020
Sun et al. CVPR 2020

EDOF Imaging
Sitzmann et al. SIGGRAPH 2018

Flat / Lensless Cameras
Boominathan et al. TPAMI/ICCP 2020
Case Study:
Neural Holography

Y. Peng, S. Choi, N. Padmanaban, G. Wetzstein "Neural Holography with Camera-in-the-loop Training", ACM SIGGRAPH Asia, 2020

S. Choi, Y. Peng, J. Kim, G. Wetzstein "Optimizing image quality for holographic near-eye displays with Michelson Holography", OSA Optica, 2021
Conventional Hologram Optimization = Phase Retrieval
Camera-in-the-loop (CITL) Hologram Optimization

[Peng et al., SIGGRAPH Asia 2020]
Wirtinger Holography

[Chakravarthula et al. 2019]

Generated offline
Captured in real-time
Our Camera-in-the-loop Optimization

Generated offline
Captured in real-time

[Peng et al., SIGGRAPH Asia 2020]
Real-time CGH with a CNN

Conventional Direct CGH (for reference)  Proposed HoloNet

[Peng et al., SIGGRAPH & SIGGRAPH Asia 2020]

computationalimaging.org
References and Further Reading

Wave Optics:

- Z. Zhang, M. Levoy, “Wigner distributions and how they relate to the light field”, ICCP 2009

Deep Optics:

See individual slides