NeuWS:Neural Wavefront Shaping for Guidestar-Free Imaging Through Static and Dynamic Scattering Media

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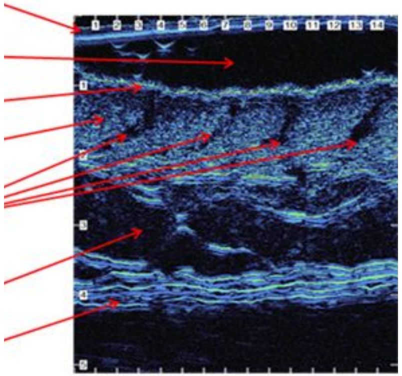
Problem

- Imaging through time varying aberrations and scattering media is one of the most important problems in optics today
  - Space-based imaging (i.e. the atmosphere)
  - Bio-imaging (i.e. soft tissue)

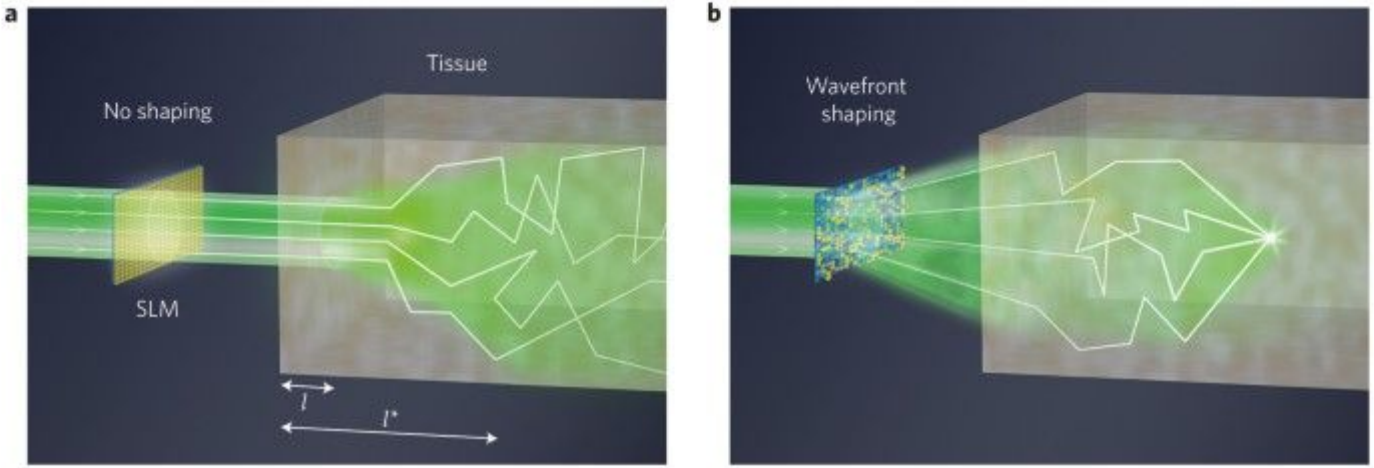
Ex. moving clouds in the sky



Layers of skin/ tissue

Goals with Current solutions

- Obtain diffraction limited imaging
  - Ideal optical system for high resolution
- Use waveshaping solutions
  - Aims to control and focus light in scattered media

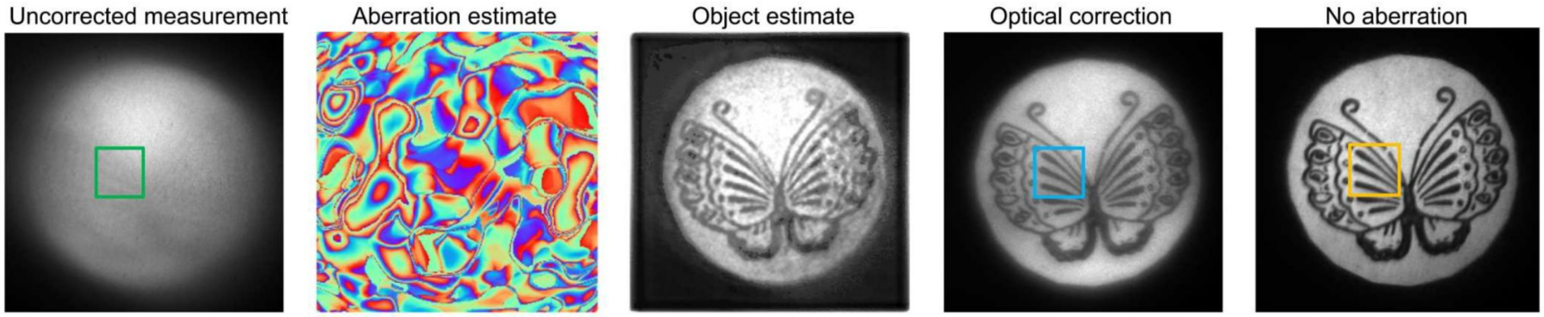


Limitations with current solutions

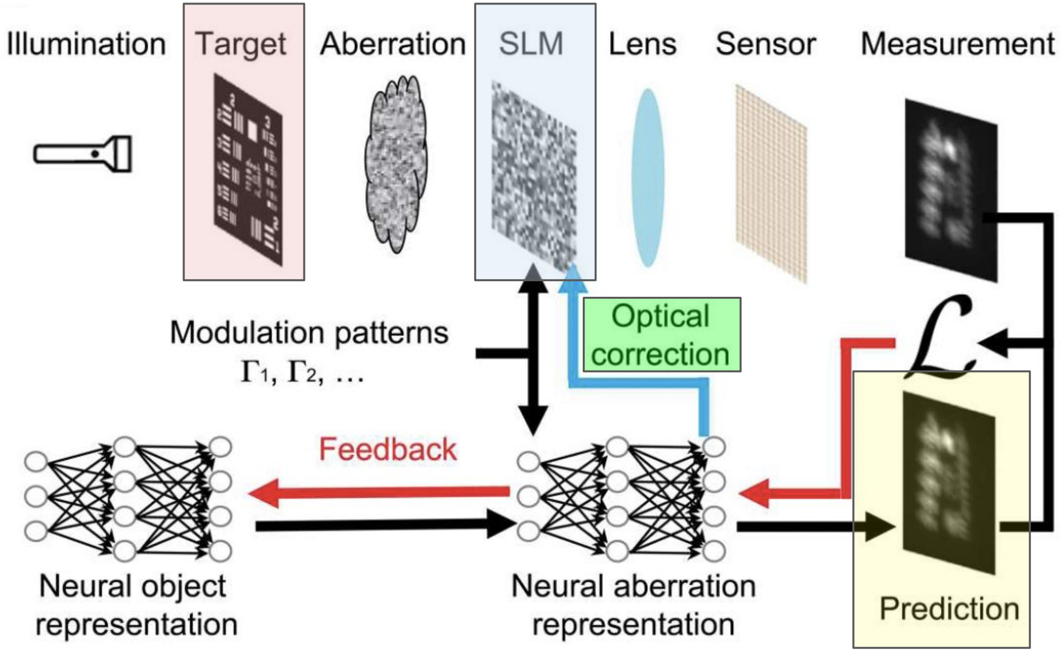
- Adaptive optics - uses waveshaping
  - Only for lower-order aberrations
- Higher-order solutions: wavefront correction
  - Requires guidestar
  - However, they rely on knowing aberrations beforehand
- Guidestar-free wavefront shaping has been tried
  - Time consuming
  - 10s of thousands of images → not practical.
- Purely computational approaches are entirely assumption based
  - Difficult to model
  - Described through chaos theory
    - Highly sensitive to initial conditions

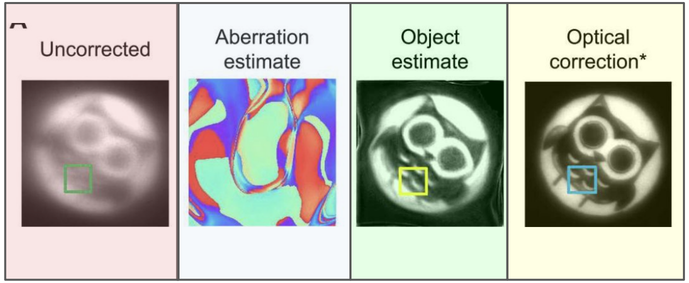
Proposed Solution: Wavefront Shaping Neural System

- Corrects for aberrations
- Combines estimation theory with neural representations
    - Jointly predicts aberration phase and object's brightness
- For static AND dynamic aberrations/ targets
- Result: high resolution, diffraction limited imaging system of a dynamic scene through time varying optical aberrations
    - No invasion, illumination, and guide-stars needed



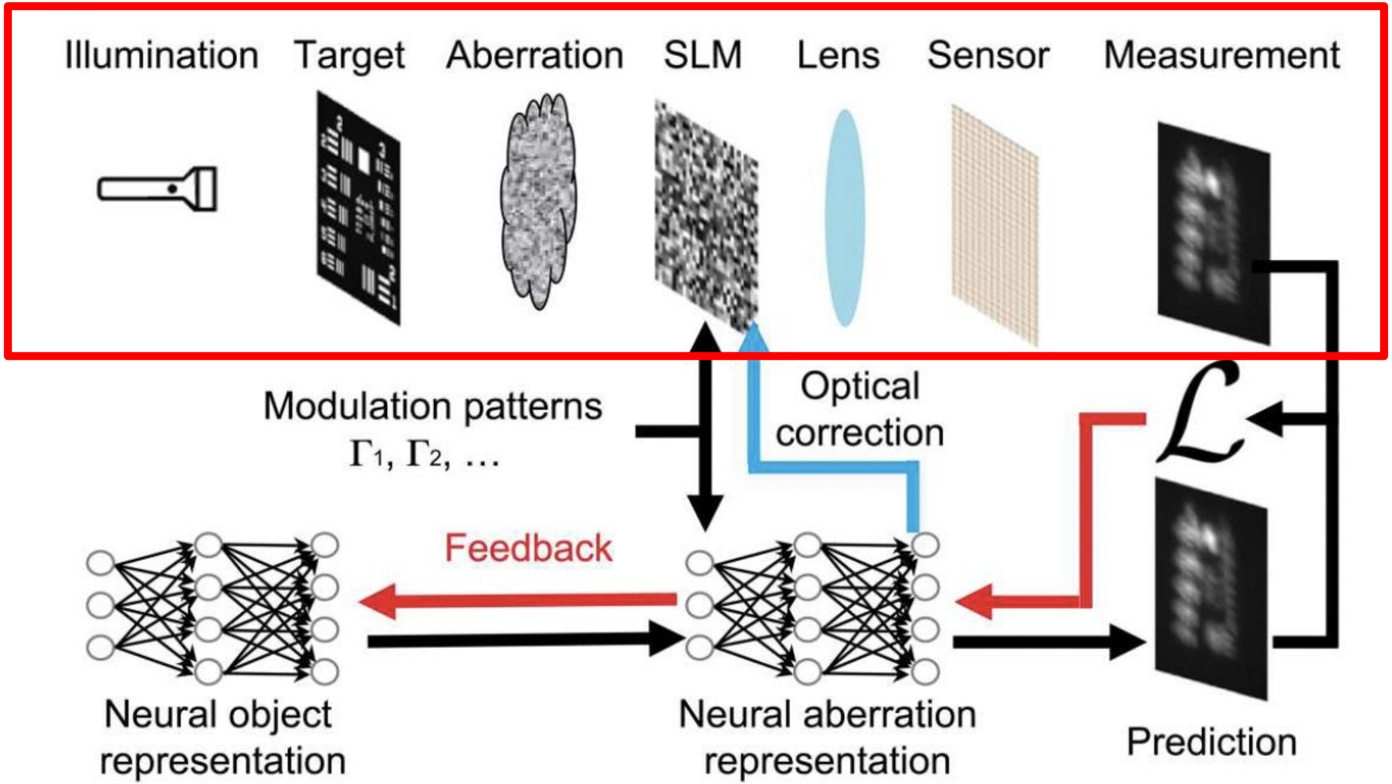
Proposed Solution cont. - Technical Model





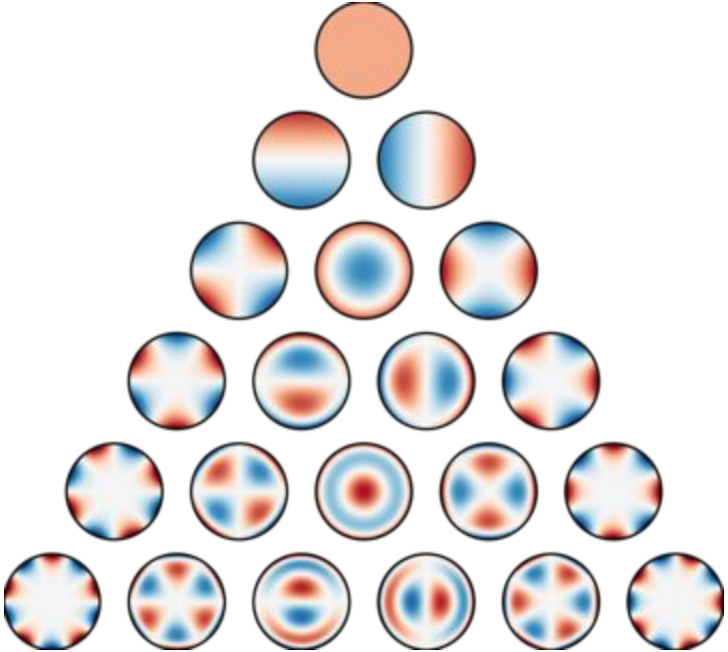
Returns higher resolution image

Optical Diagram



Optical Setup

- Light Source
  - Temporally Coherent
  - Spatially Incoherent
  - 532nm
- Spatial Incoherence
  - Rotating Diffuser
  - Speckle Reducer
- Spatial Light Modulator (SLM)
  - Superposition of first 15 Zernike polynomials
  - Corrects phase



Optical Setup Cont.

- Image Capture
  - 1384px x 1036px
  - 90ms - 120ms exposure time
- Dynamic Object Translation
  - Translation stage
  - Rotation Stage

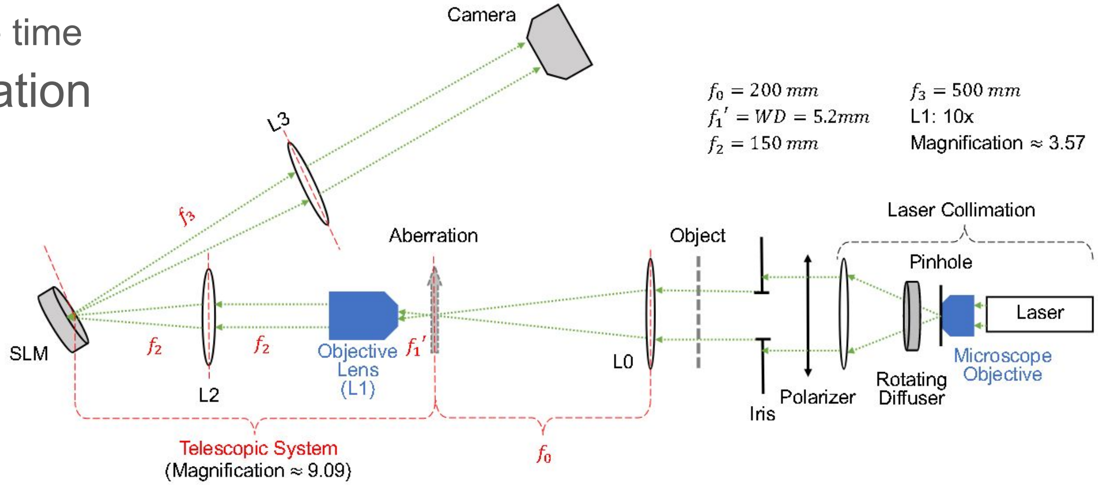


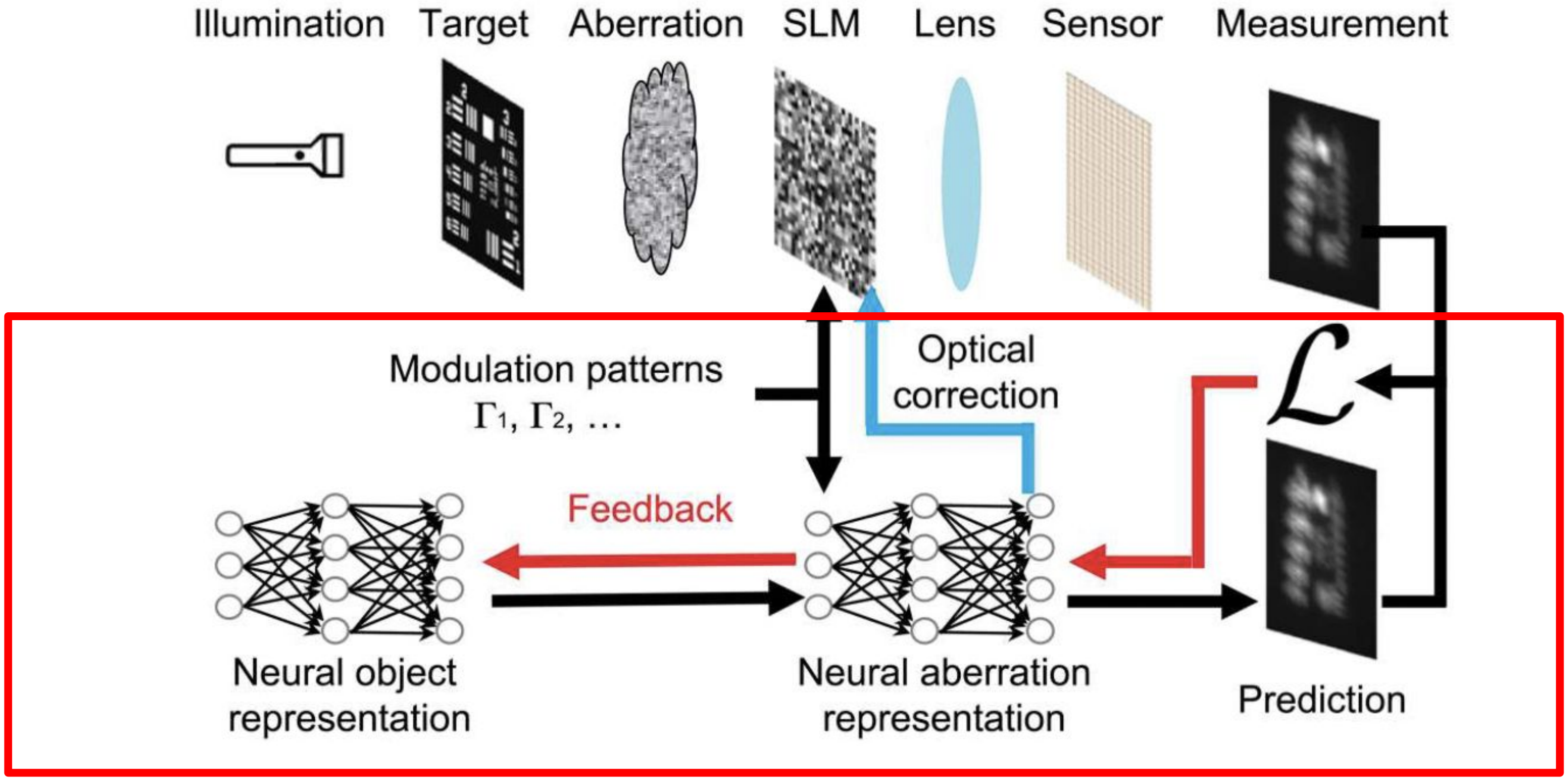
Figure S1: **Optical Setup.** A spatially incoherent light source (narrowband laser passing through a rotating diffuser and laser speckle reducer) illuminates an object-of-interest. Light from the object then passes through an aberration before making its way through our optical system and onto our camera. The SLM is imaged onto the same optical plane as the aberration.

Optical Forward Model

- Model in Fourier Domain
  - Corrective patterns applied in aperture plane
- Relevant Variables
  - O - Object
  - H - Transfer Function
  - Z - Random Noise
  - M - Aperture Function (defined by SLM)
  - Phi - Phase of Aberrations
  - Gamma - Corrective Phase Mask

$$I_i = O_o * H_i + Z_i \text{ with } H_i = \left| \mathcal{F}\left[M \circ e^{j(\Phi_o + \Gamma_i)} \right] \right|^2$$

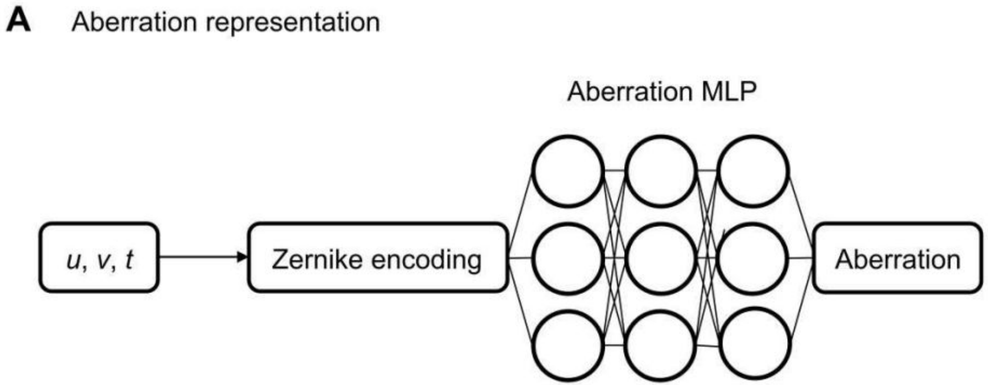
Neural Representations



Neural Aberration Representation

Main Goal: Predict Phase of Aberrations Distorting Object

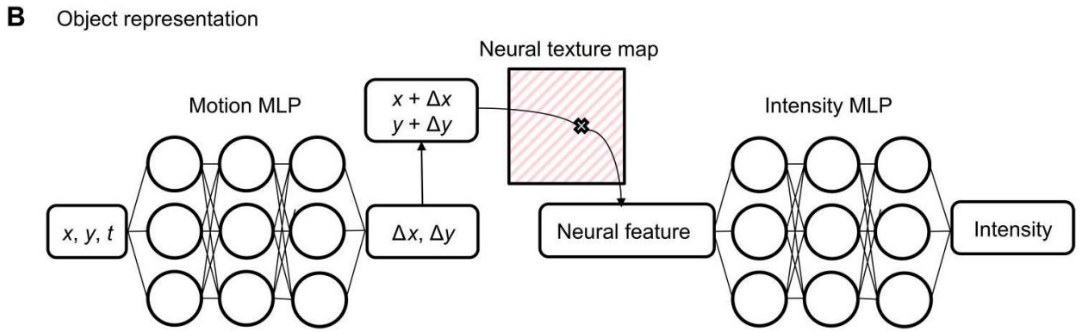
- Reparameterization of (x,y) to (u,v)
  - Enables temporal encoding (t)
  - Neural Representations are continuous
- Zernike Encoding
  - First 28 polynomials
- Multilayer Perceptron (MLP)
  - 8 hidden layers (tunable)
  - Hidden dimension of 32
  - Leaky ReLU activation



Neural Object Representation

Main Goal: Predict object brightness from input

- Step 1: Predict Object motion (dx, dy)
  - MLP (8 layers, 32 hidden dimensions)
- Step 2: Determine feature at x+dx, y+dy
  - Project onto learnable feature map
- Step 3: Predict brightness/intensity
  - MLP (2 layers, 32 hidden dimensions)



Why Use Neural Texture Map?

- Continuous
  - Not limited to discrete basis
  - Requires fewer MLP layers
- Easy to Differentiate
  - Loss landscape is smoother
  - Continuity enables differentiation

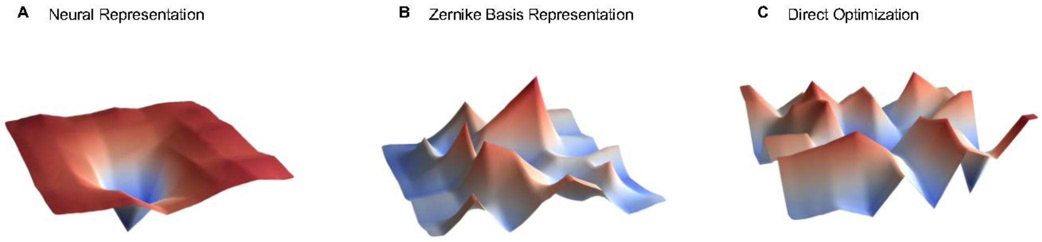


Figure S4: **Loss Landscape with Various Aberration Representations.**

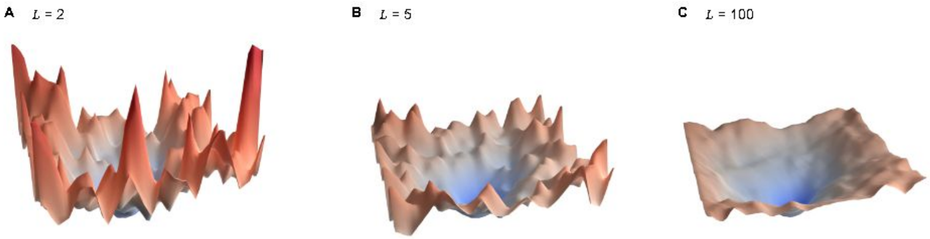


Figure S5: **Loss Landscape with Varying Numbers of Observations L.**

Optimize Something!

- Two loss functions
  - Static object
  - Dynamic object
- Sum of least squared error
  - Image
  - Predicted object

$$\mathrm{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \tilde{y}_i)^2$$

$$\mathcal{L}_{\mathrm{static}}(O, \Phi) = \sum_{i=1}^{L} \| I_i - O * |\mathcal{F}[M \circ e^{j(\Phi+\Gamma_i)}]|^2 \|^2$$

$$\mathcal{L}_{\mathrm{dynamic}}[O(t_{\mathrm{i}}), \Phi(t_{\mathrm{i}})] = \sum_{i=1}^{L} \| I(t_{\mathrm{i}}) - O(t_{\mathrm{i}}) * |\mathcal{F}\{M \circ e^{j[\Phi(t_{\mathrm{i}})+\Gamma_{\mathrm{i}}]}\}|^2 \|^2$$

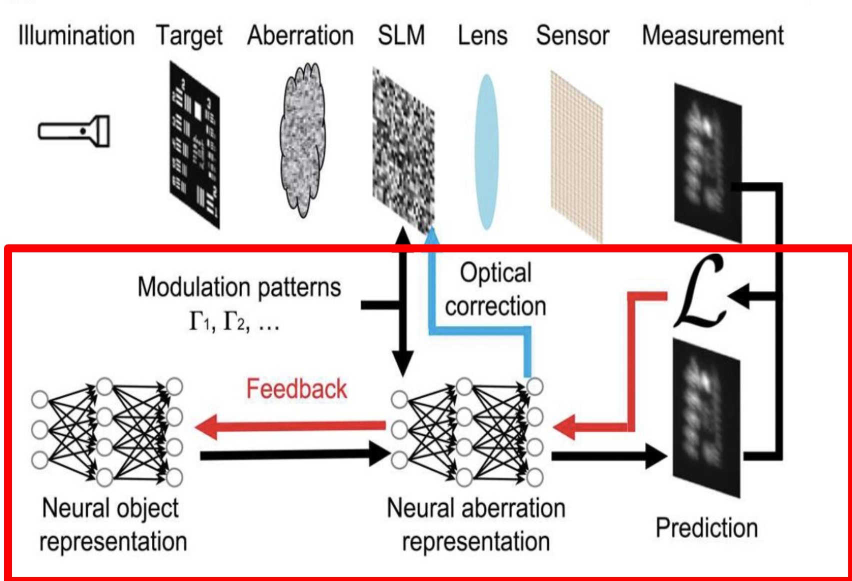
O - Object
H - Transfer Function
Z - Random Noise
M - Aperture Function
Phi - Phase of Aberrations
Gamma - Corrective Phase Mask
I - Collected Image

Connecting Neurons

- Randomly assign L modulation patterns on SLM
  - Capture L measurements
- Perform Stochastic Gradient Descent
  - Batch size = 4
  - Adam optimizer
  - Learning rate = 1e-3
  - 1000 epochs

$$\mathcal{L}_{\text{static}}(O,\Phi) = \sum_{i=1}^{L} \| I_i - O * |\mathcal{F}[M \circ e^{j(\Phi+\Gamma_i)}]|^2 \|^2$$

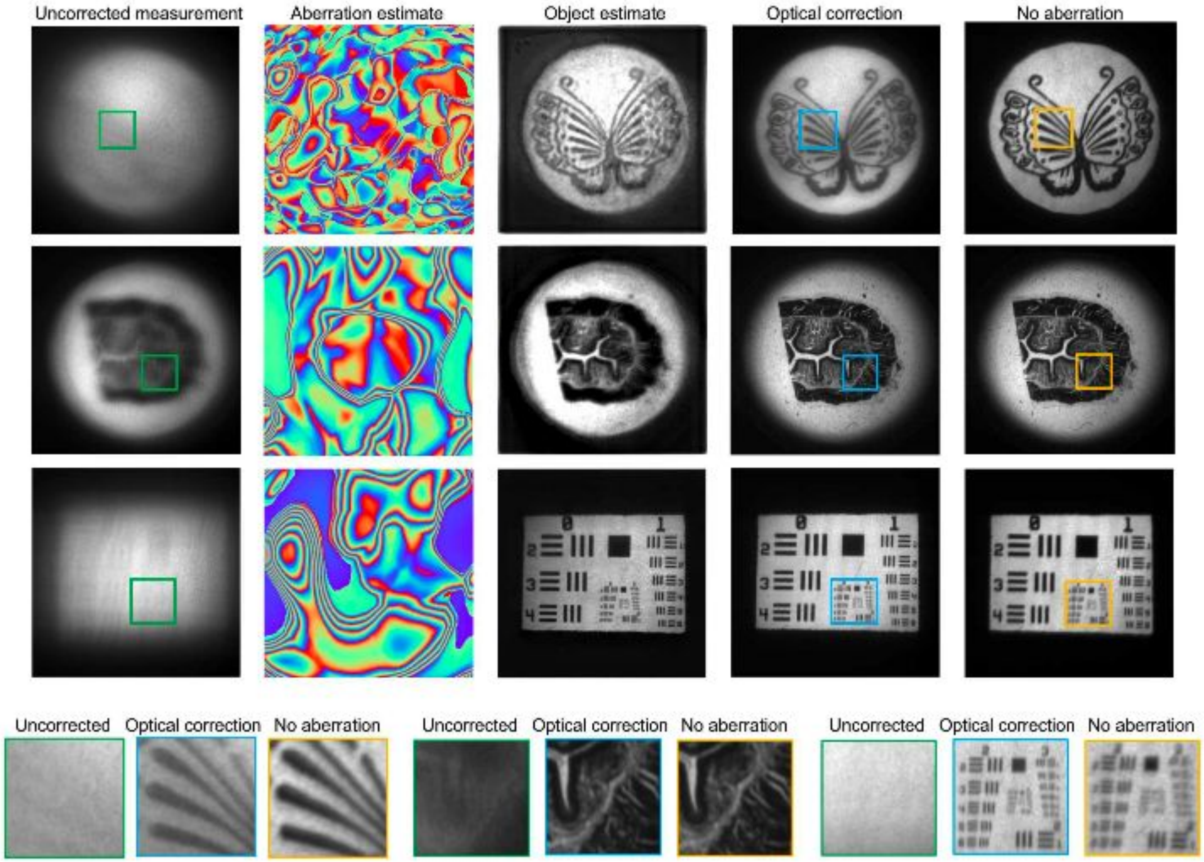
$$\mathcal{L}_{\text{dynamic}}[O(t_i),\Phi(t_i)] = \sum_{i=1}^{L} \| I(t_i) - O(t_i) * |\mathcal{F}\{M \circ e^{j[\Phi(t_i)+\Gamma_i]}\}|^2 \|^2$$



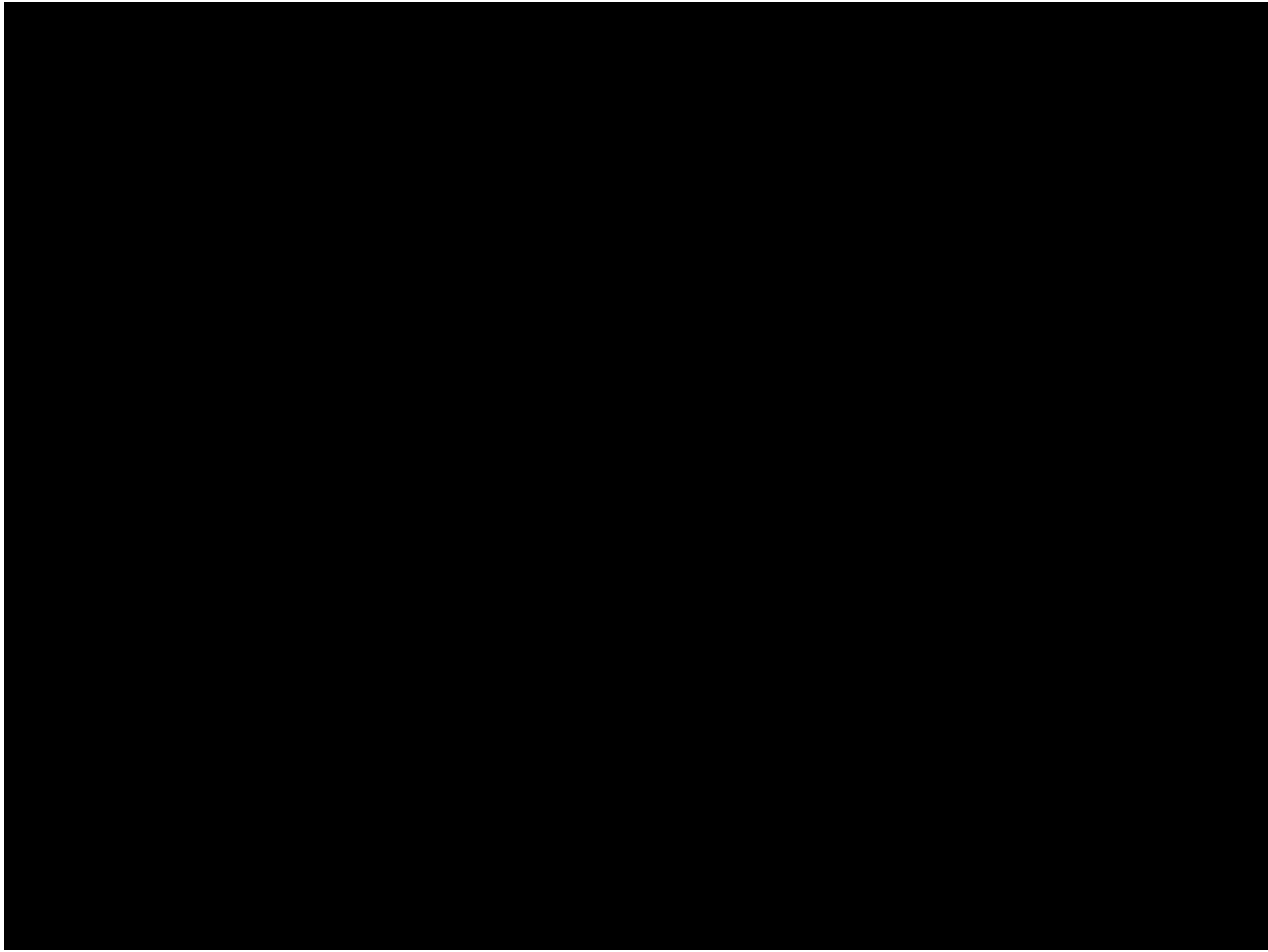
Validating NeuWS

Static objects with static aberrations	Dynamic objects with static aberrations	Static objects with dynamic aberrations	Dynamic objects with dynamic aberrations
Minimise loss function Estimate aberrations and object brightness Conjugate of aberration projected on SLM to correct aberration	Modify loss function for time-varying object Minimise with $O(t)$, Φ	Modify loss function for time-varying aberration Minimise with O, $\Phi(t)$	Modify loss function for time-varying object and aberration Minimise with $O(t)$, $\Phi(t)$

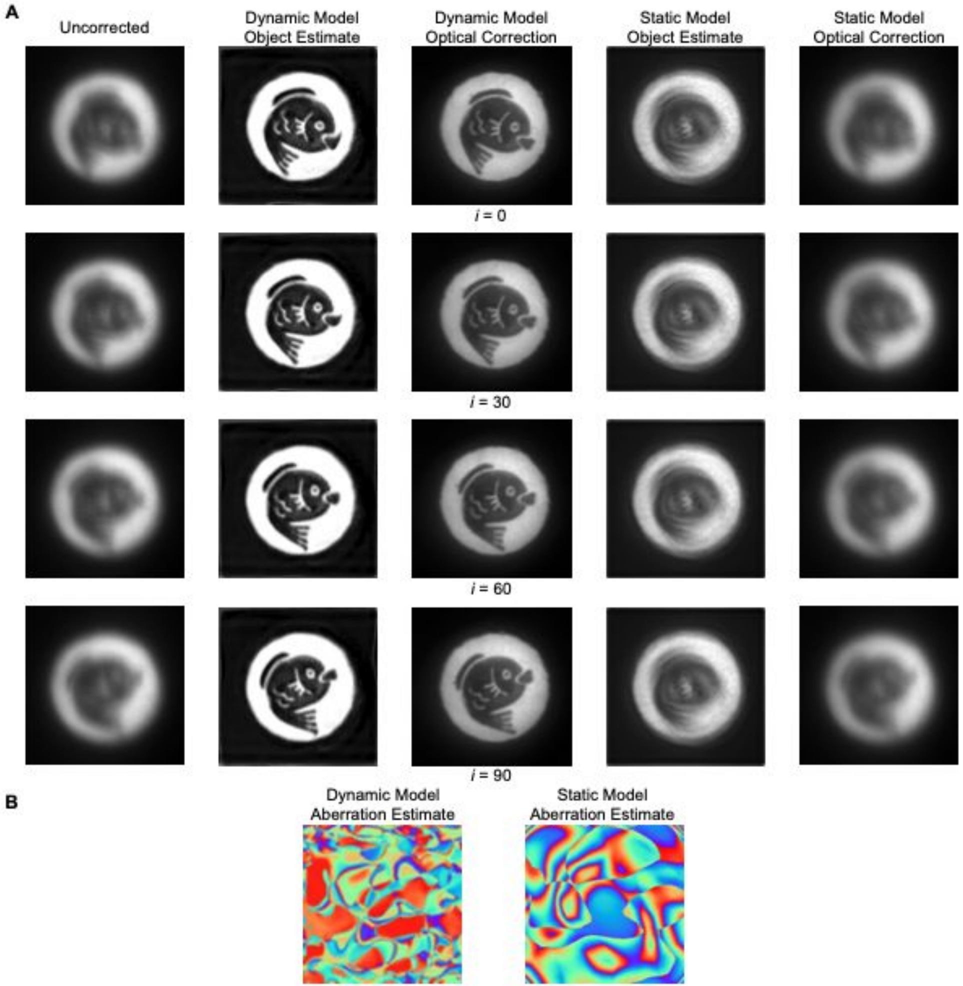
Static Objects with Static Aberrations



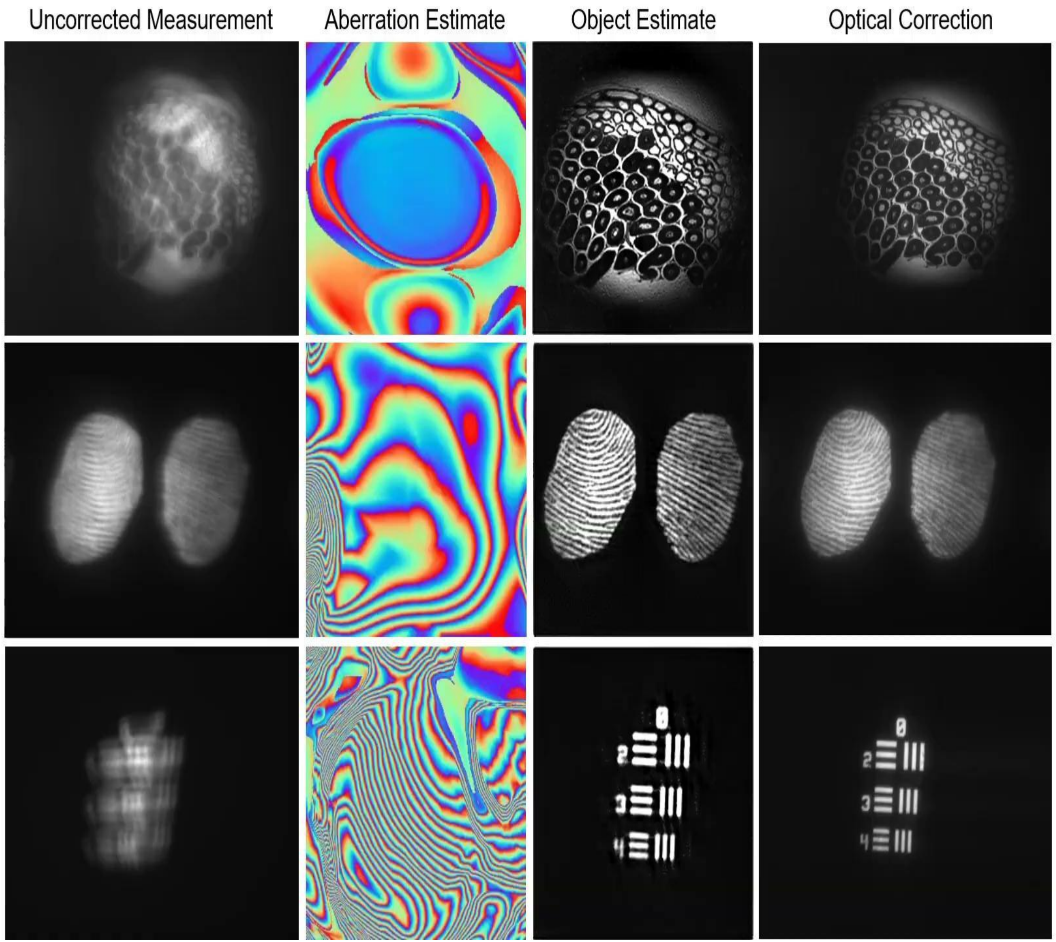
Dynamic Objects with Static Aberrations



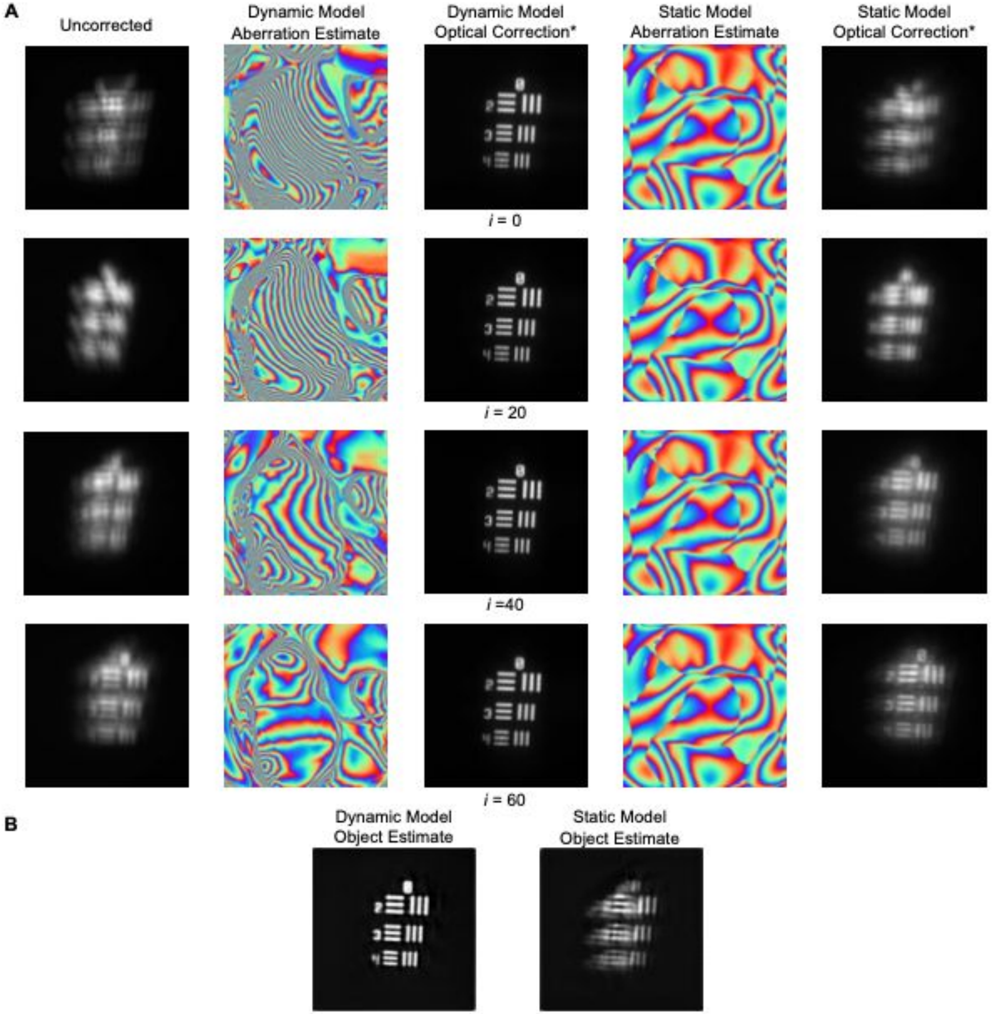
Dynamic vs Static Modelling of Dynamic Objects



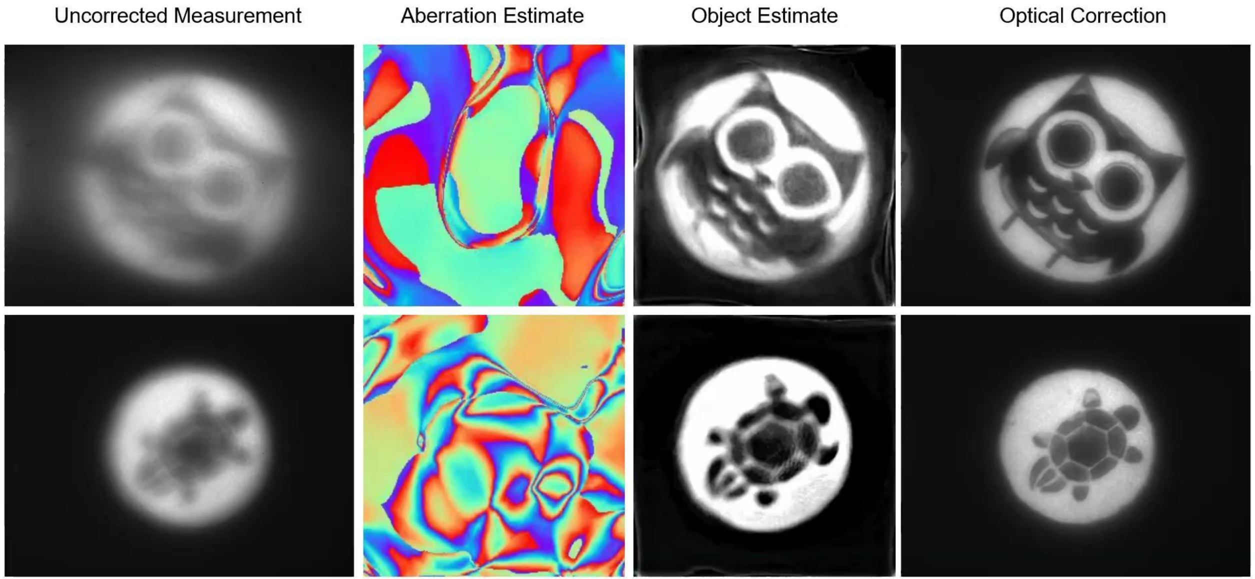
Static Objects with Dynamic Aberrations



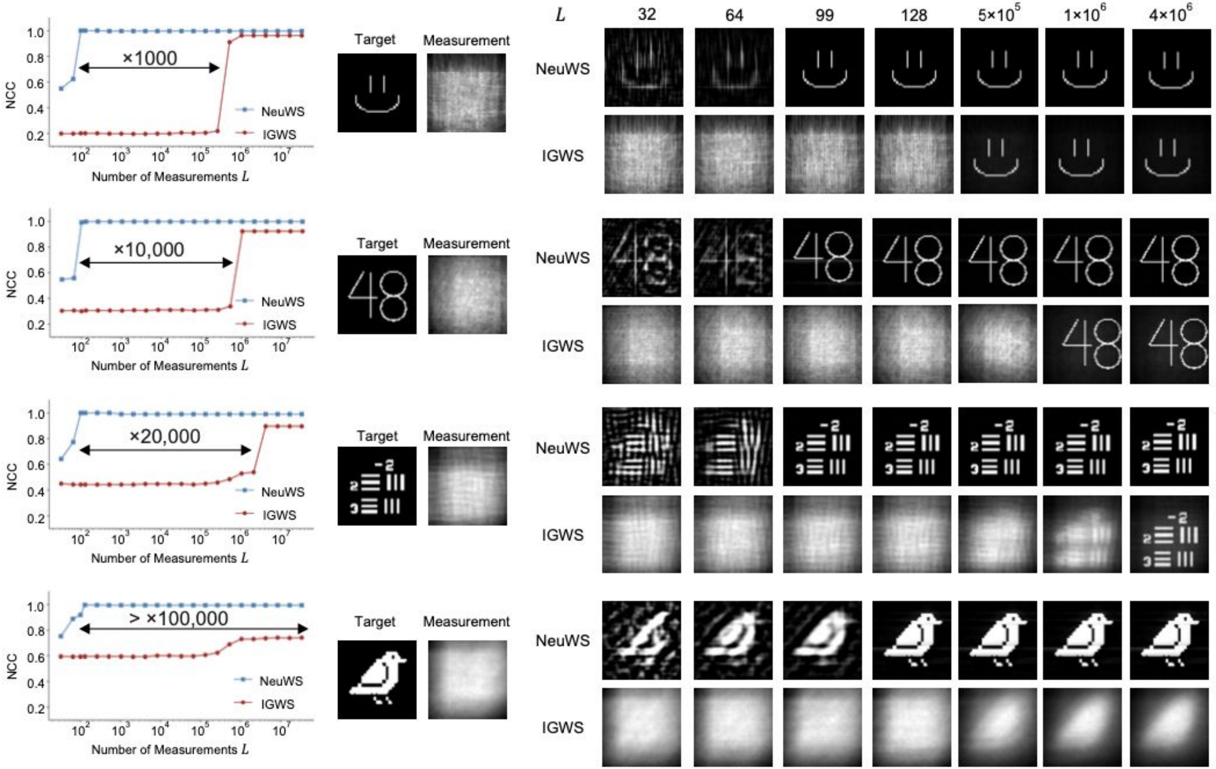
Dynamic vs Static Modelling of Dynamic Aberrations



Dynamic Objects with Dynamic Aberrations



NeuWS vs Image-Guided Wavefront Shaping



NeuWS as a Methodology

Strengths:

- Lower order and higher order aberrations
- Not restricted to binary, sparse or simple scenes
- Diffraction-limited, static and dynamic objects and aberrations
- Post-capture corrections as an alternative for the latency problem

Weaknesses:

- Translation corrections only for dynamic aberrations
- Isoplanatic aberrations and planar scenes

NeuWS in Practice

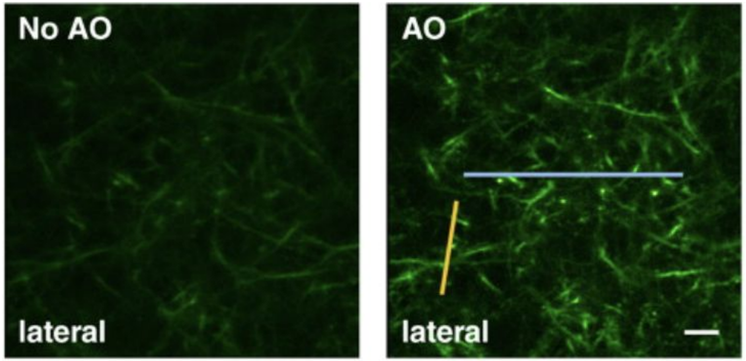
Applications:

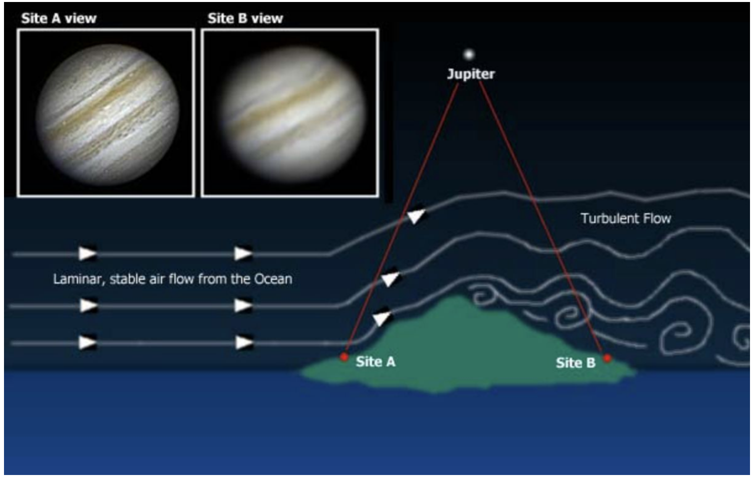
High resolution imaging of cells and tissues:

- Presence of coverslip
- Thick samples
  - Multiple interfaces
  - Multiple subregions

Ground-based astronomical imaging

- Atmospheric turbulence
- Some systems assume a model of refractive index fluctuations





To Summarize the Wavefront Shaping Neural System

<u>Goal</u>

Obtain diffraction-limited optical imaging through time varying and scattering media

<u>Constraints</u>

(1) Knowledge about the aberration (2) Time

<u>Proposed Solution: NeuWS</u>

- Combines NN, wavefront shaping, and image capture
- High resolution
- Fast
- Versatile applications→ static & dynamic targets and aberrations

Thanks!

Citations

[1] B. Y. Feng et al., “Neuws: Neural wavefront shaping for guidestar-free imaging through static and dynamic scattering media,” *Science Advances*, vol. 9, no. 26, Jun. 2023. doi:10.1126/sciadv.adg4671

[2] The Atmosphere and Observing - A Guide to Astronomical Seeing, https://www.cloudynights.com/articles/cat/articles/how-to/the-atmosphere-and-observing-a-guide-to-astronomical-seeing-r543 (accessed Apr. 8, 2024).

[3] N. Ji, T. R. Sato, and E. Betzig, “Characterization and adaptive optical correction of aberrations during in vivo imaging in the mouse cortex,” *Proceedings of the National Academy of Sciences*, vol. 109, no. 1, pp. 22–27, Dec. 2011. doi:10.1073/pnas.1109202108