Utilization of Deep Learning Methods for Automatic Reconstruction of Quantitative Phase Images in Non-telecentric Digital Holographic Microscopy

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Optical Imaging Research Lab

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Digital Holographic Microscopy (DHM)

- Principle: DHM offers advantages of recording and reconstructing complex object distributions (e.g., both amplitude and phase information)
- Advantages of DHM
  - Capable of 3-D reconstructions of samples in a single shot.
  - Label-free imaging technique
  - Perfect candidate for live-cell imaging.
- Recording: interferometry (e.g., interference between two wavefronts – object and reference waves)

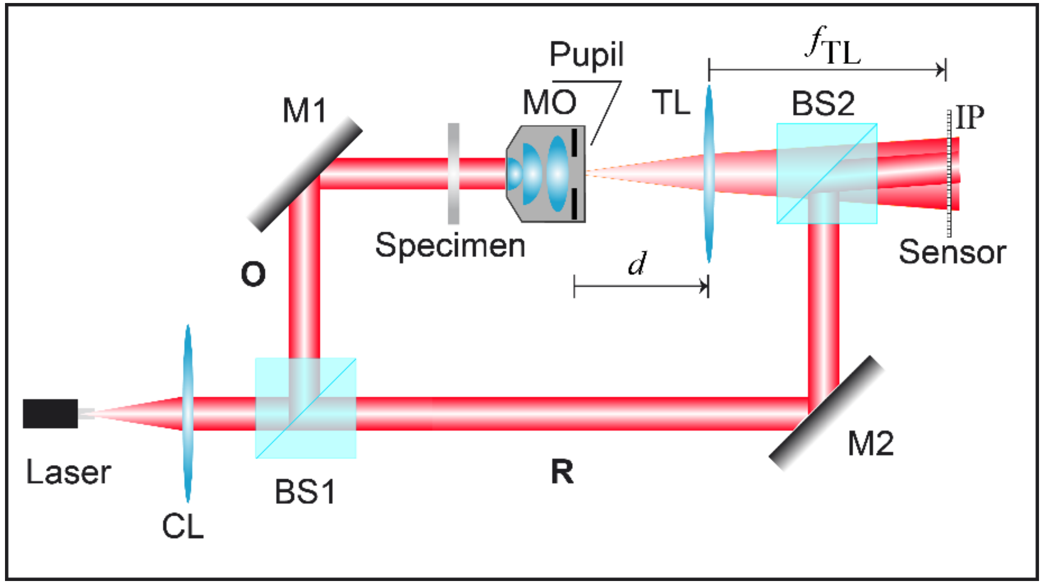

FIGURE. Optical configuration of an off-axis DHM system based on a modified Mach-Zehnder interferometer. In a general case, the microscopic objective (MO) lens and the tube lens (TL) are arranged in non-telecentric mode (d ≠ fTL). The remaining components of the system are denoted as: CL, converging lens; BS, beamsplitter; IP, image plane; M, mirror; O, object wave; R, reference wave.

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Non-telecentric DHM systems provide phase images distorted by a spherical phase term introduced by the optical imaging system

Complex amplitude distribution at the image plane (IP)

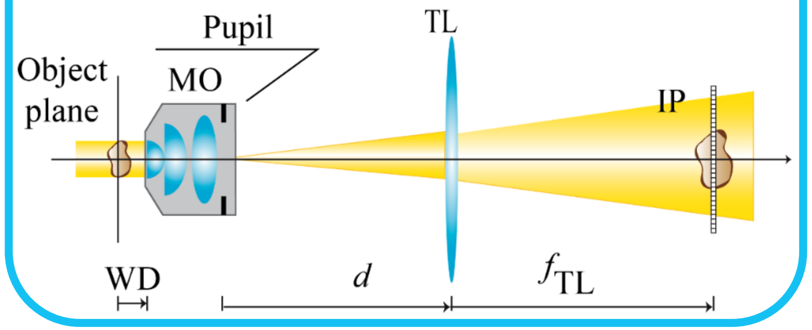
$$U_{IP}(\boldsymbol{x}) \propto \frac{1}{M^2} \exp\left(i \frac{k}{2C} |\boldsymbol{x}|^2 \right) \times \left\{ O\left(\frac{\boldsymbol{x}}{M} \right) \otimes_2 \tilde{p}\left(\frac{\boldsymbol{x}}{\lambda f_{TL}} \right) \right\}$$

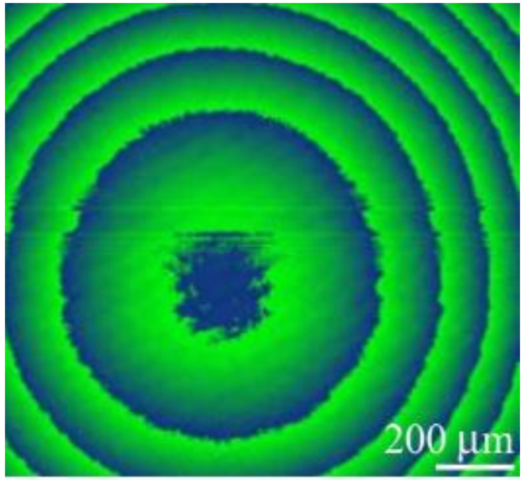
$$M = -f_{TL} / f_{MO}$$

$$C = f_{TL}^2 / (f_{TL} - d)$$

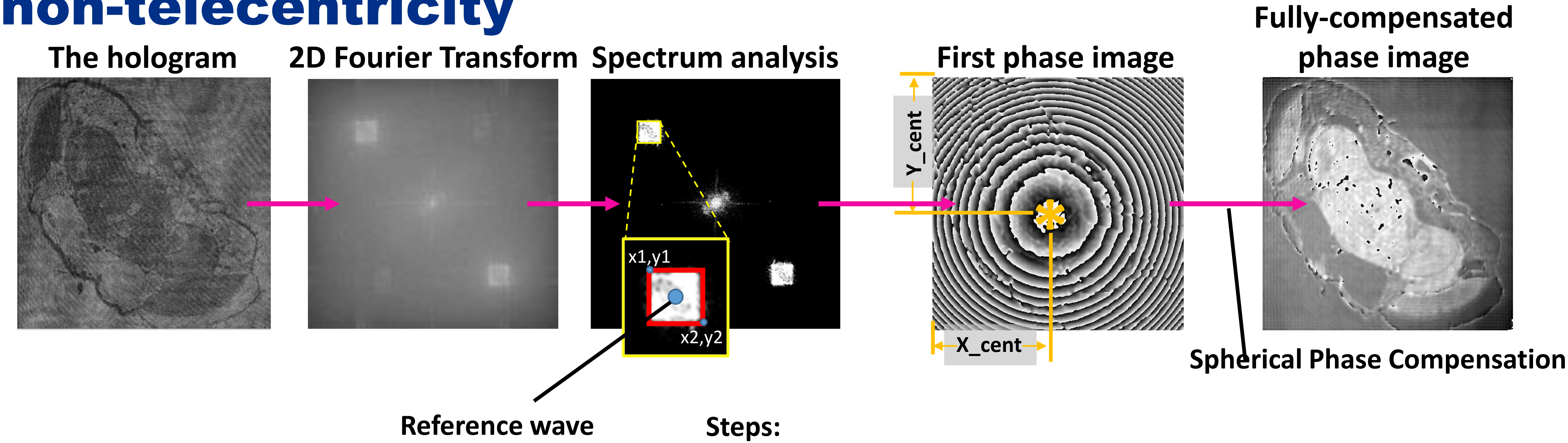
- The non-telecentric DHM systems are **shift-variant**.
- The phase measurement depends on the object position within the whole field of view.

Non-Telecentric DHM





Tedious algorithm to compensate the spherical phase term introduced by the non-telecentricity



Steps:

1. Spectrum filtering with a rectangular filter from (x1,y1,) to (x2,y2)
2. Inverse Fourier Transform
3. Compensation of the tilt with a digital reference wave with position is the centroid of the rectangular filter

Min *et al.*, *Opt. Letters* 42, 227 (2017).

Use of Deep Learning to correct the spherical distortions

- We propose the application of deep learning artificial intelligence algorithms for automatically correcting and reconstructing images from holograms obtained with non-telecentric Mach-Zehnder DHM systems.
- Convolutional neural network model: the **pix2pix** conditional Generative Adversarial Network (cGAN).
- The model that was trained on a simulated, and then evaluated on the accuracy of its reconstruction ability.

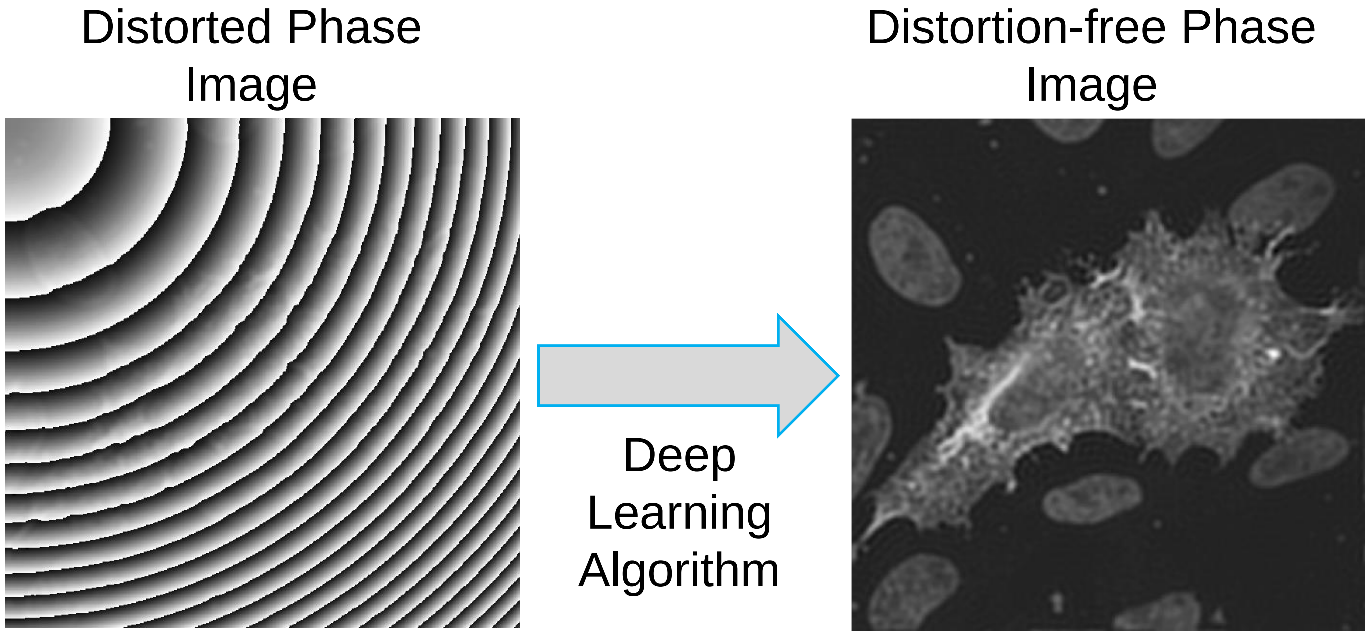
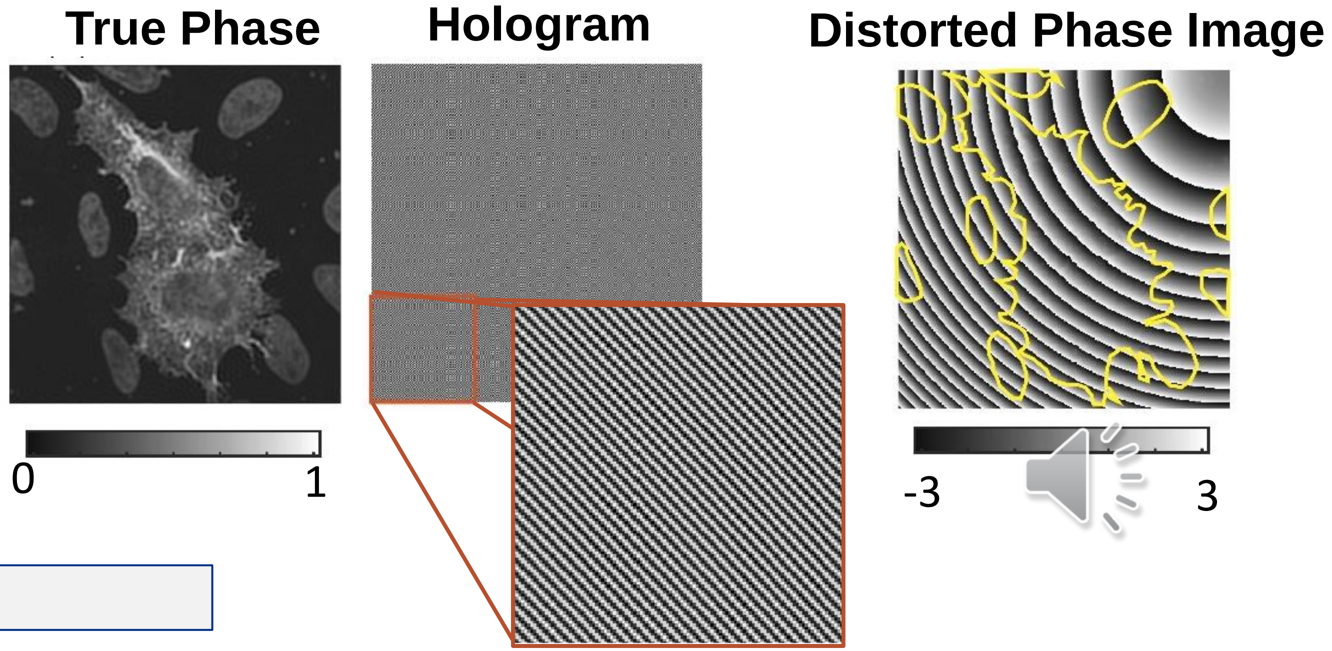


FIGURE. Description the proposed system and its intended functionality. Left image portrays the distorted image resulting from spherical aberrations and right image is the desired computationally corrected image.

Generation of the simulated dataset

- Kinome Atlas dataset from the Cell Image Library [8]: with 907 total images, of size 512x512 pixels
- Dual-path Mach-Zehnder DHM
- Hologram: $h(x, \mathrm{y}; z = 0) = |u(\mathrm{x}, \mathrm{y})|^2 + |r(x, \mathrm{y})|^2 + u(x, \mathrm{y})r^*(x, \mathrm{y}) + u^*(x, \mathrm{y})r(x, \mathrm{y})$
- Object beam: $u(x, \mathrm{y}) = \frac{1}{M^2} exp[\left(\mathrm{j}\frac{k}{2C}(x^2 + y^2)\right) \times [o(\frac{x}{M}, \frac{y}{M}) \otimes_2 \ P(\frac{x}{\lambda f_{TL}}, \frac{y}{\lambda f_{TL}})]]$
- 3 simulated aberrations where *C* = 3,500, 4000, 5000

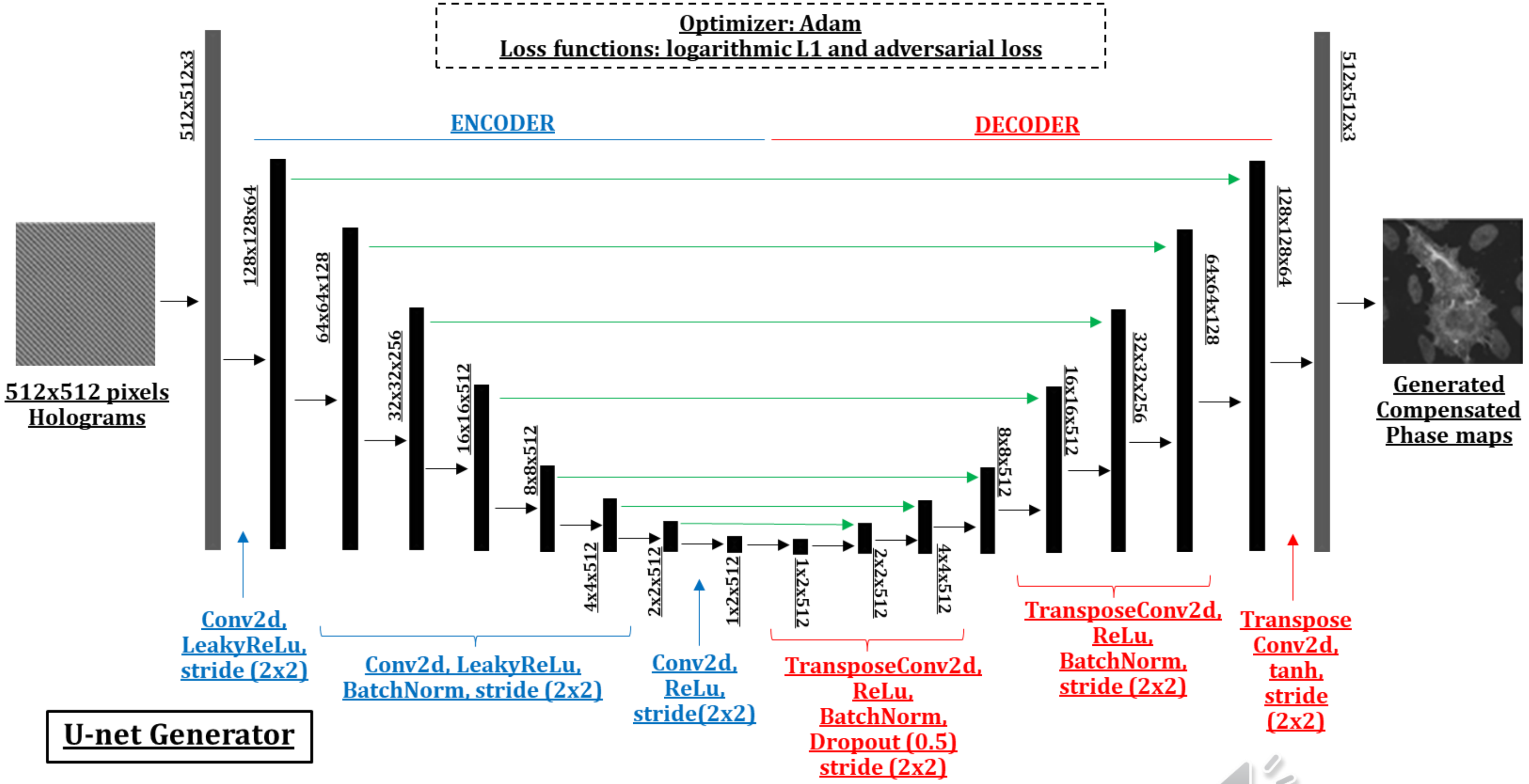
FIGURE. Illustration of the non-telecentric DHM dataset using HeLa cells from the Kinome Atlas dataset:



Isola *et al.*, IEEE *CVPR* (2017).

The PIX2PIX Conditional Generative Adversarial Network (cGAN)

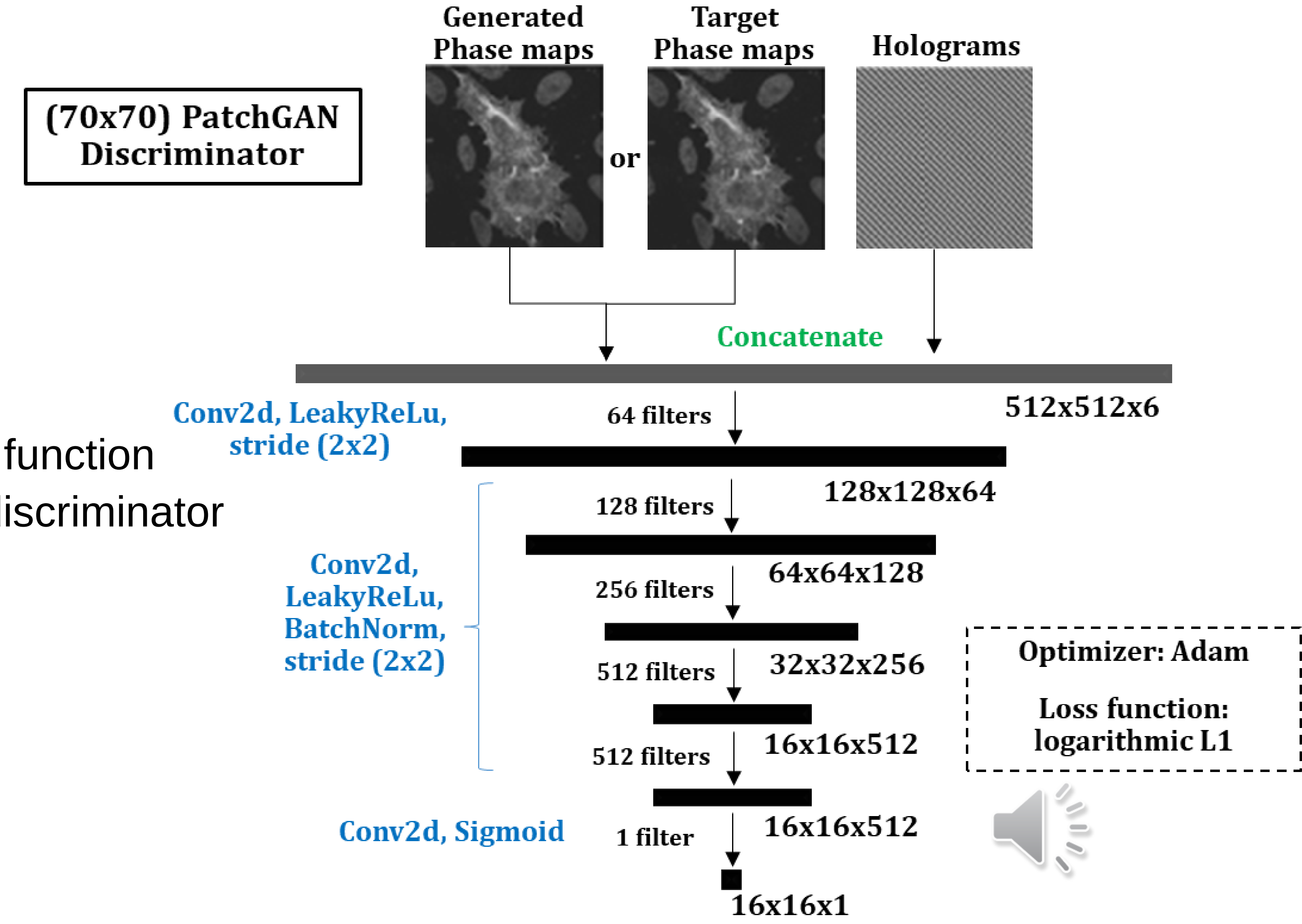
- pix2pix cGAN
- cGAN are a U-Net & CNN
- U-Net: Generator
- Encoding
  - Convolution 4x4 filters
  - Batch normalization
  - LeakyReLU activation
  - Final layer: tanh
- Decoding
  - ReLU



U-Net Architecture for the Generator of that cGAN.

The PIX2PIX Conditional Generative Adversarial Network (cGAN)

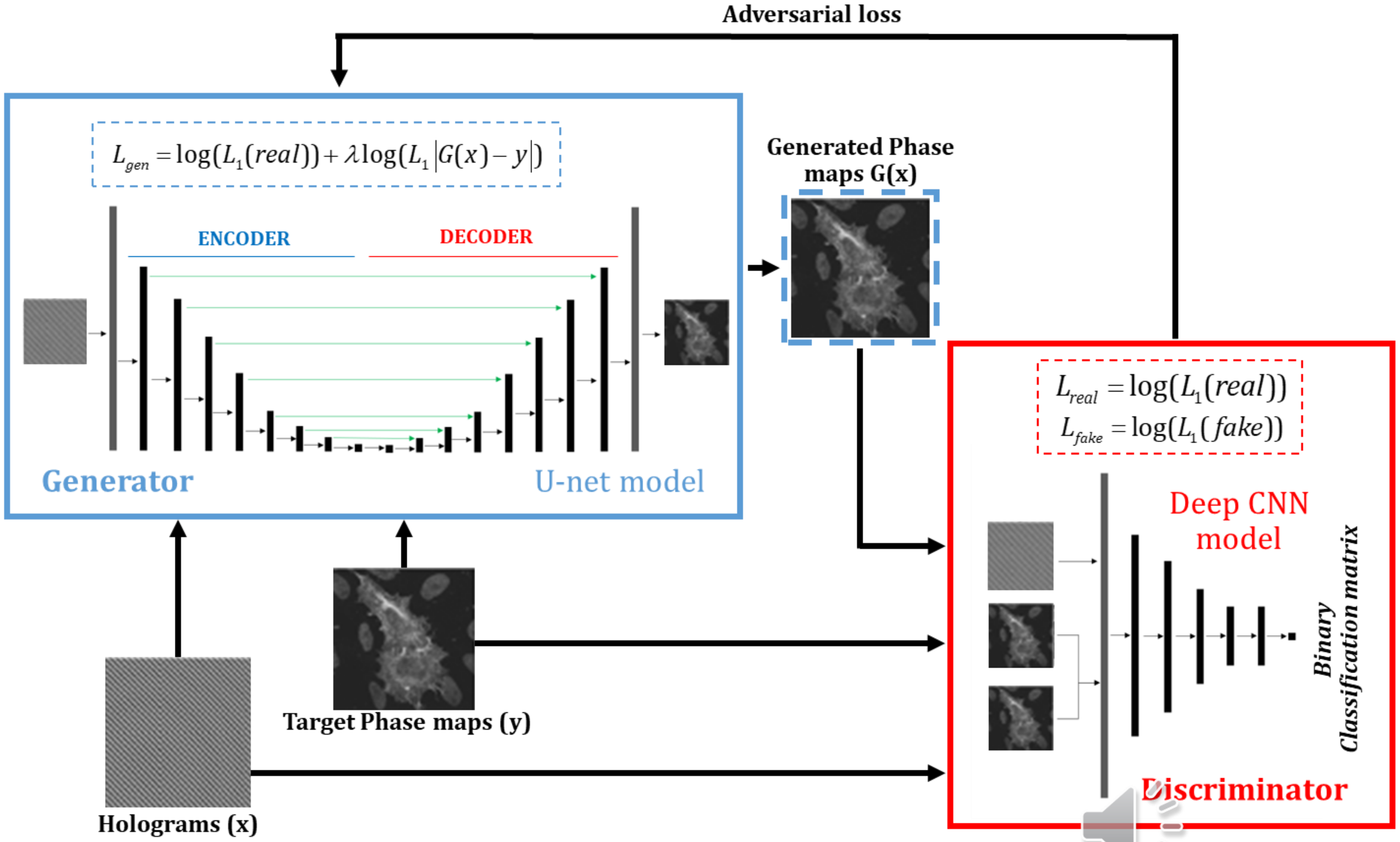
- pix2pix cGAN
- cGAN are a U-Net & CNN
- CNN: Discriminator
  - 4x4 filters
  - LeakyReLU
  - Last layer uses a sigmoid function
  - Generator needs to trick discriminator



PatchGAN CNN Architecture for the Discriminator of that cGAN.

Metrics and Hyperparameters used to train the cGAN

- Mean Absolute Error (MAE) by the generator
- Binary cross-entropy used by the discriminator
- Adam optimizer
  - Learning rate: 0.0002
  - beta-1 value of 0.5
  - beta-2 value of 0.999
- Training Procedure:
  - 100 epochs
  - batch size of 1



Results – average Peak Signal-to-Noise Ratio (PSNR)

- Training/testing split of 80/20.
- Peak signal-to-noise ratio (PSNR)
- For Each epoch, the average PSNR of 15 random images in the training and test dataset is computed.
- The behavior of PSNR values is are quite noisy.
- Trend of the PSNR fluctuates within a mean value after epoch 30.

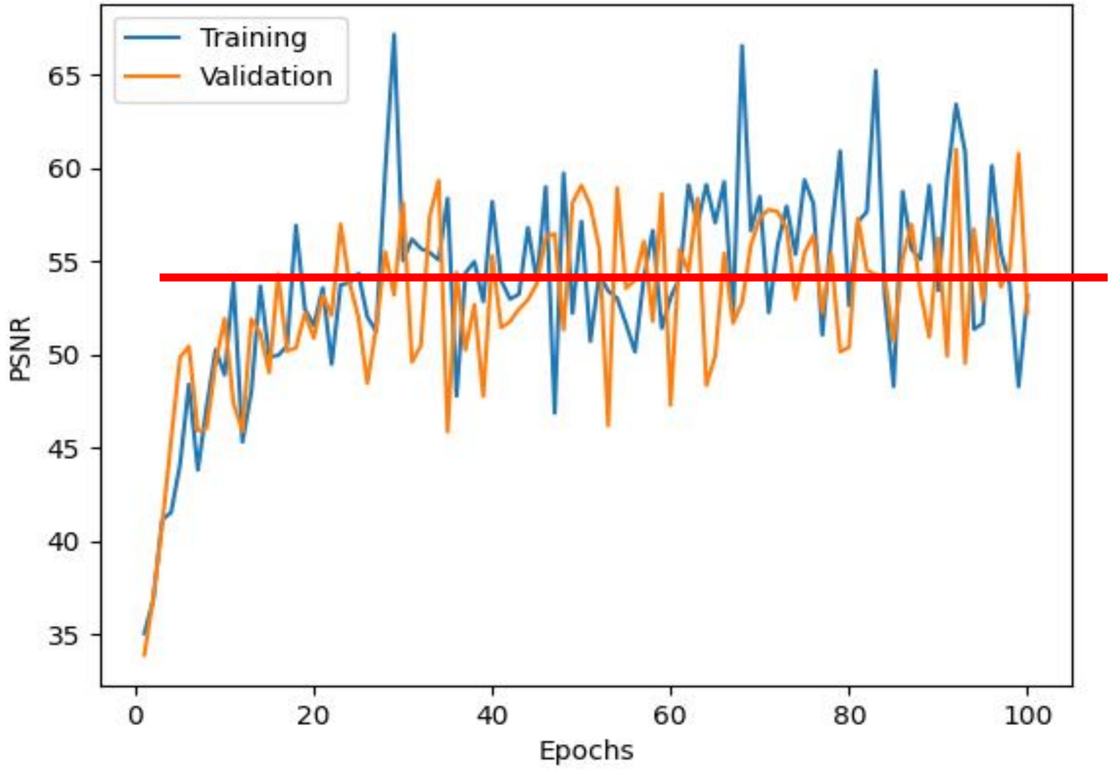
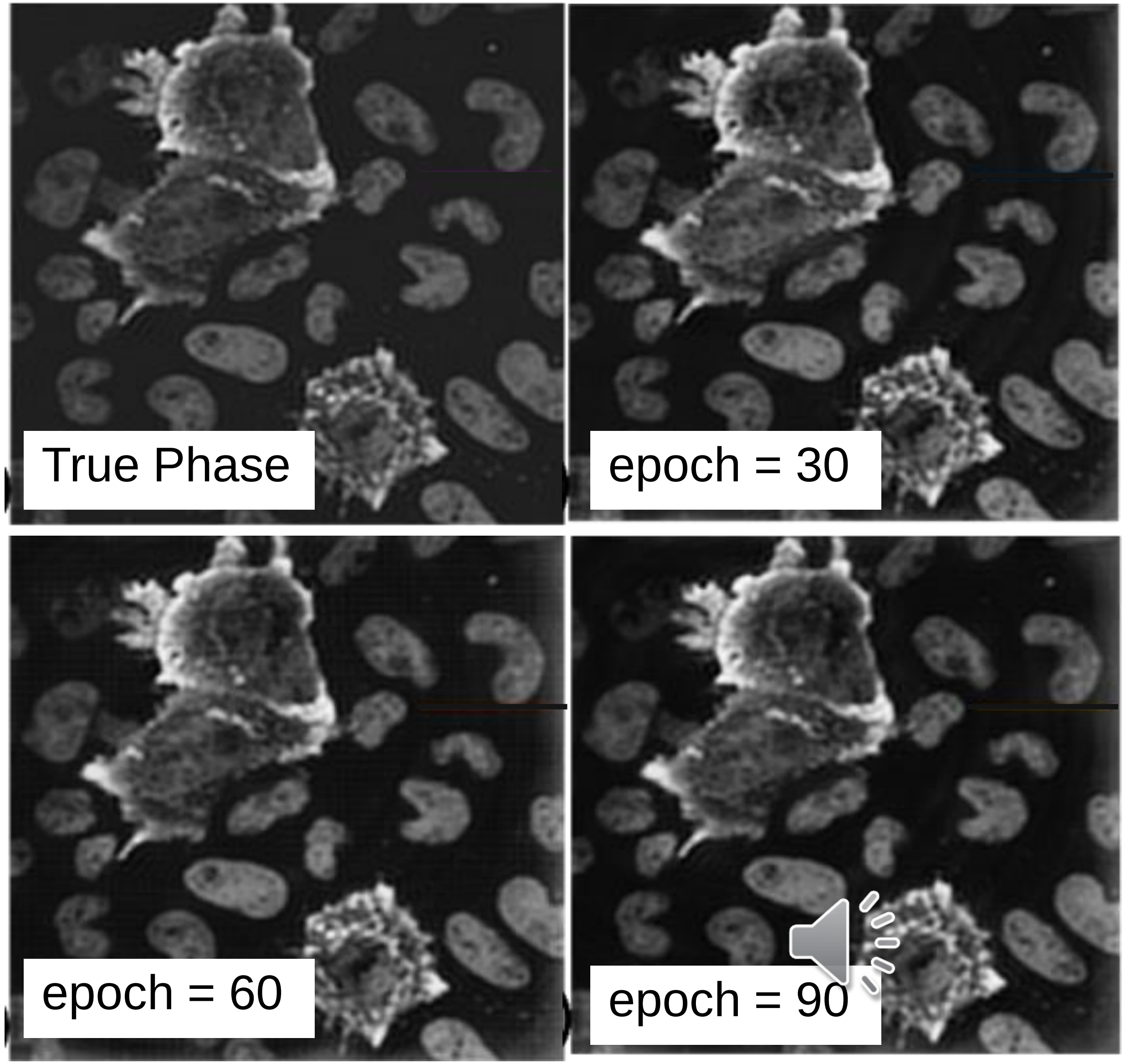


FIGURE. Peak Signal-to-Noise Ratio (PSNR) vs Number of Epochs of the Training and Testing datasets.

Results – true versus predicted phase images

- Qualitatively, the agreement between the true and predicted phase images is high.



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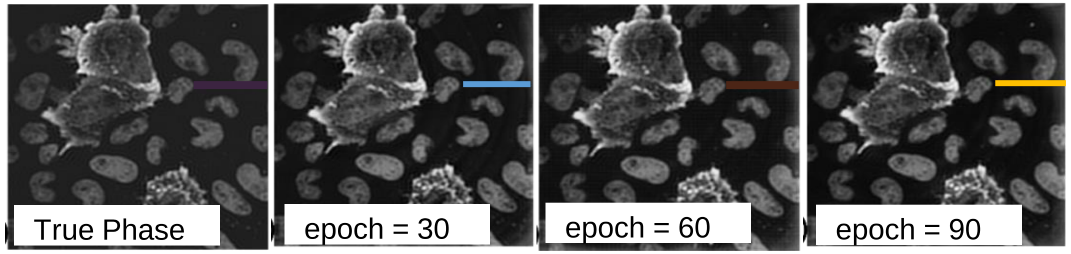
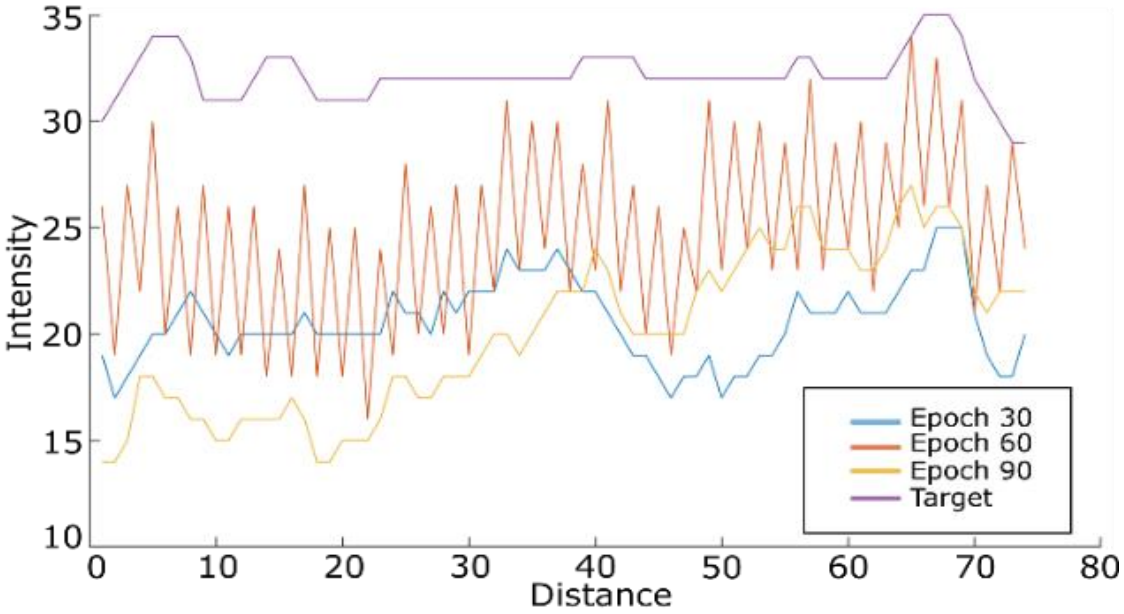
Results – true versus predicted phase images

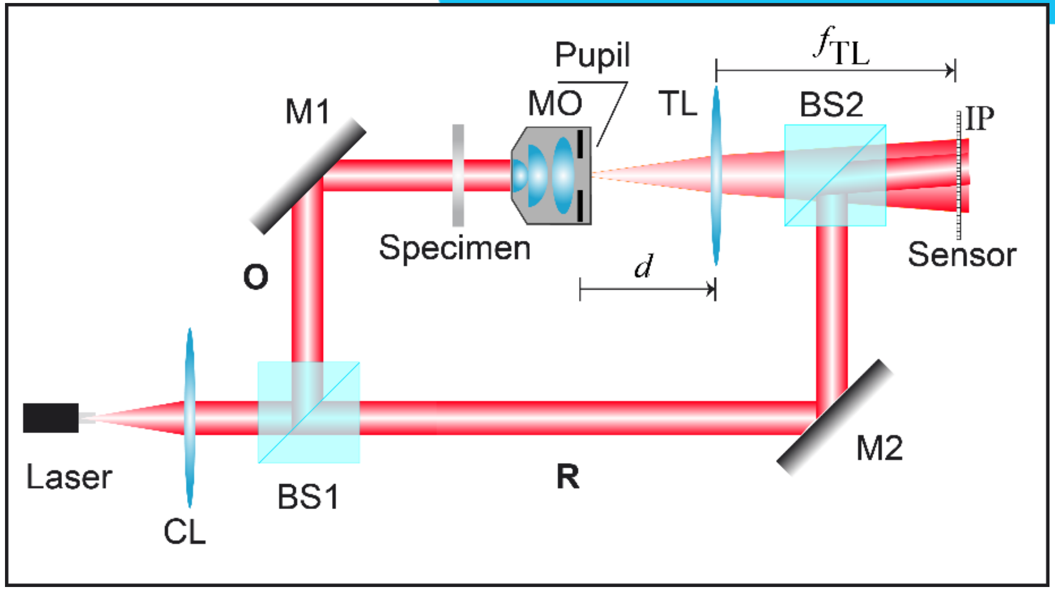
- Qualitatively, the agreement between the true and predicted phase images is high.
- The cGAN network introduces some undesired artifacts
  - *In all three epochs, there is a very dim low frequency ringing effect that is not present in the actual phase image.*
- In epoch 60, we observed a high frequency grid effect as well .





Conclusions

- DHM is widely used by the biomedical community for imaging of thin label-free samples and analyze the 3D phase images from a single recorded image.



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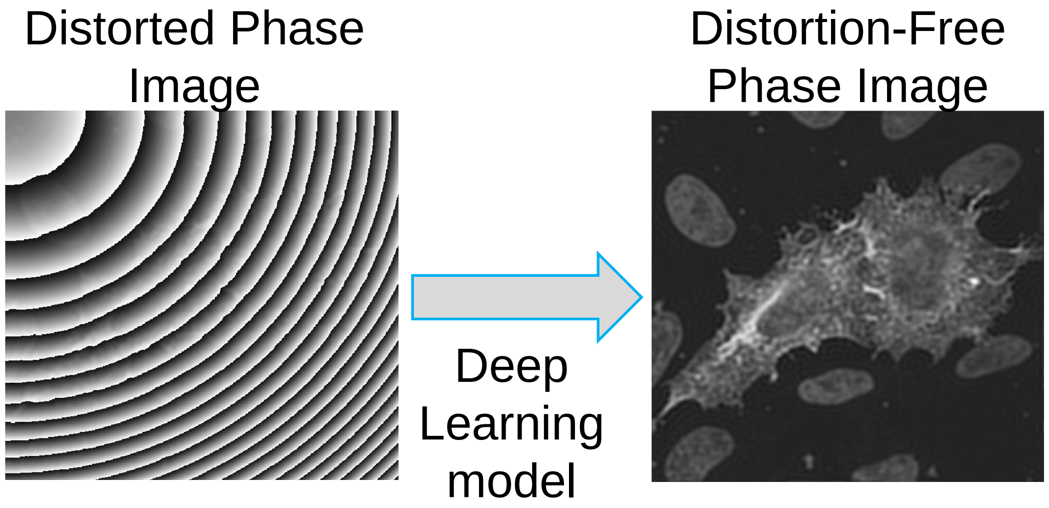
- Non-telecentric DHM systems are shift variant systems, distorting the phase images with a spherical phase term.



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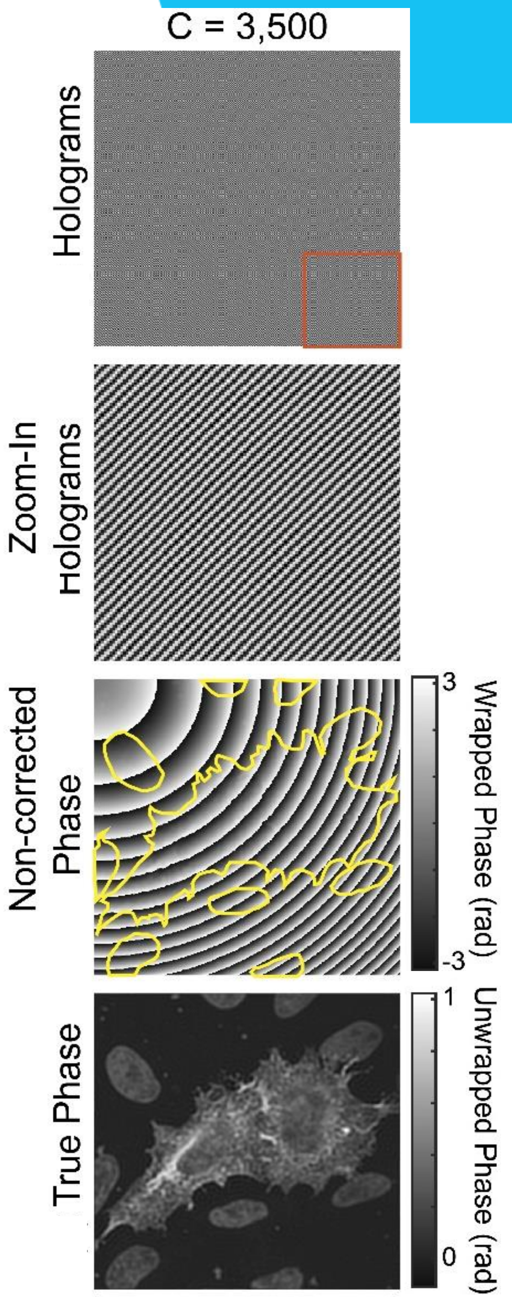
- ❑ Non-telecentric DHM systems are shift variant systems, distorting the phase images with a spherical phase term.
- ❑ This study investigate the use of a cGAN learning-based model to automatically reconstruct simulated holograms captured by non-telecentric DHM systems, including correction of the spherical aberrations.



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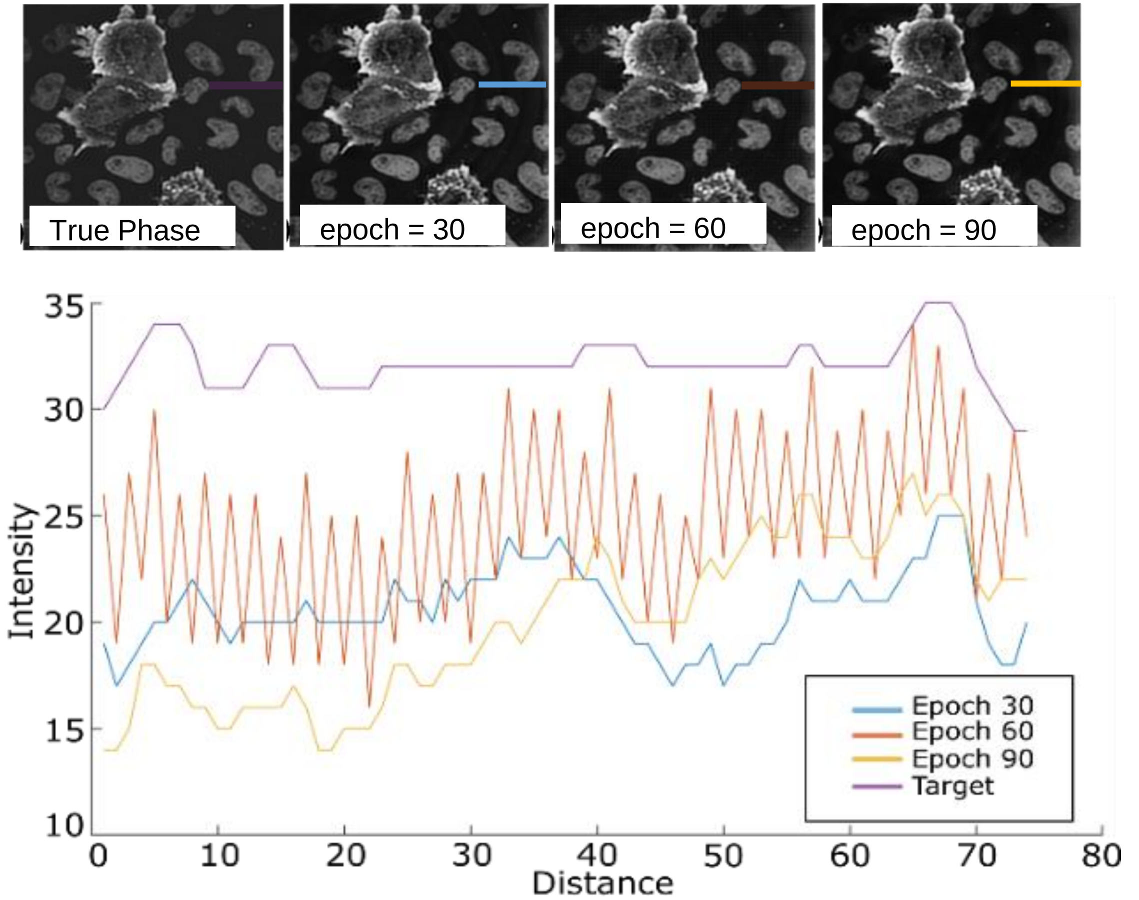
- ❑ This study investigate the use of a cGAN learning-based model to automatically reconstruct holograms captured by non-telecentric DHM systems, including correction of the spherical aberrations.
- ❑ The trained cGAN model reconstructs phase images with a high similarity (e.g., minor artifacts with respect to the true phase).



Thanks…

Q&A