

## Abstract

- In recent years, the paradigm in designing efficient phase reconstruction algorithms has shifted from optimization-based models to data-driven ones inspired by deep learning.
- Project aims to develop a phase recovery algorithm using tools and ideas from machine learning.
- The first steps of the project are to simulate the data acquisition process and test our algorithm via numerical experiments. From there, we will evaluate the practicality of the method on experimental data.
- This approach will provide higher quality and computationally cheaper phase images in comparison to those produced today, advancing the STEM community in understanding biology in terms of cells and tissues.

## What is phase?

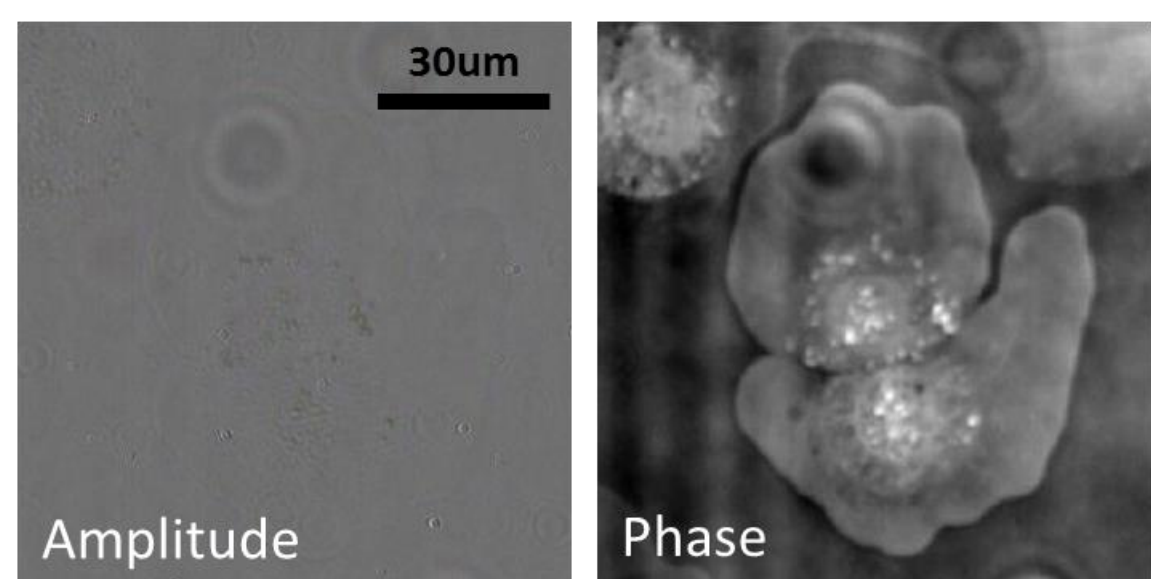


Figure 1. Amplitude and Phase [1].

### Introduction:

- Phase is a property of waves; two waves with the same frequency are "in phase" if they have the same phase and therefore line up everywhere; waves with the same frequency but different phases are "out of phase."
- However, our eyes and cameras can only detect intensity (i.e., squared-amplitude) values, so they cannot measure phase directly
- Critical to biology, as it is directly related to shape and density maps for most cells and thin tissue samples

### Existing Technique:

- **Overview:** Transport-of-Intensity Equation method requires one to record a set of defocus images to measure the variation of intensity. Weighted phase reconstruction algorithm is proposed based on the reconstruction, yielding a phase map. The method is nonlinear and combines different ranges of spatial frequencies in a regularized fashion<sup>[2]</sup>.
- **Problem:** The inverse of the measurements with the noise causes an issue in results. Creating an inverse of the measurements that involve noise in the data enhances the noise in the final image, which causes discrepancies as we look at the final phase image.

## Goals

- Developing a phase recovery algorithm that is guided by the tools and ideas developed for machine learning.
- Providing *higher quality phase images while being computationally cheaper* than those produced today.

## Algorithm Implementation

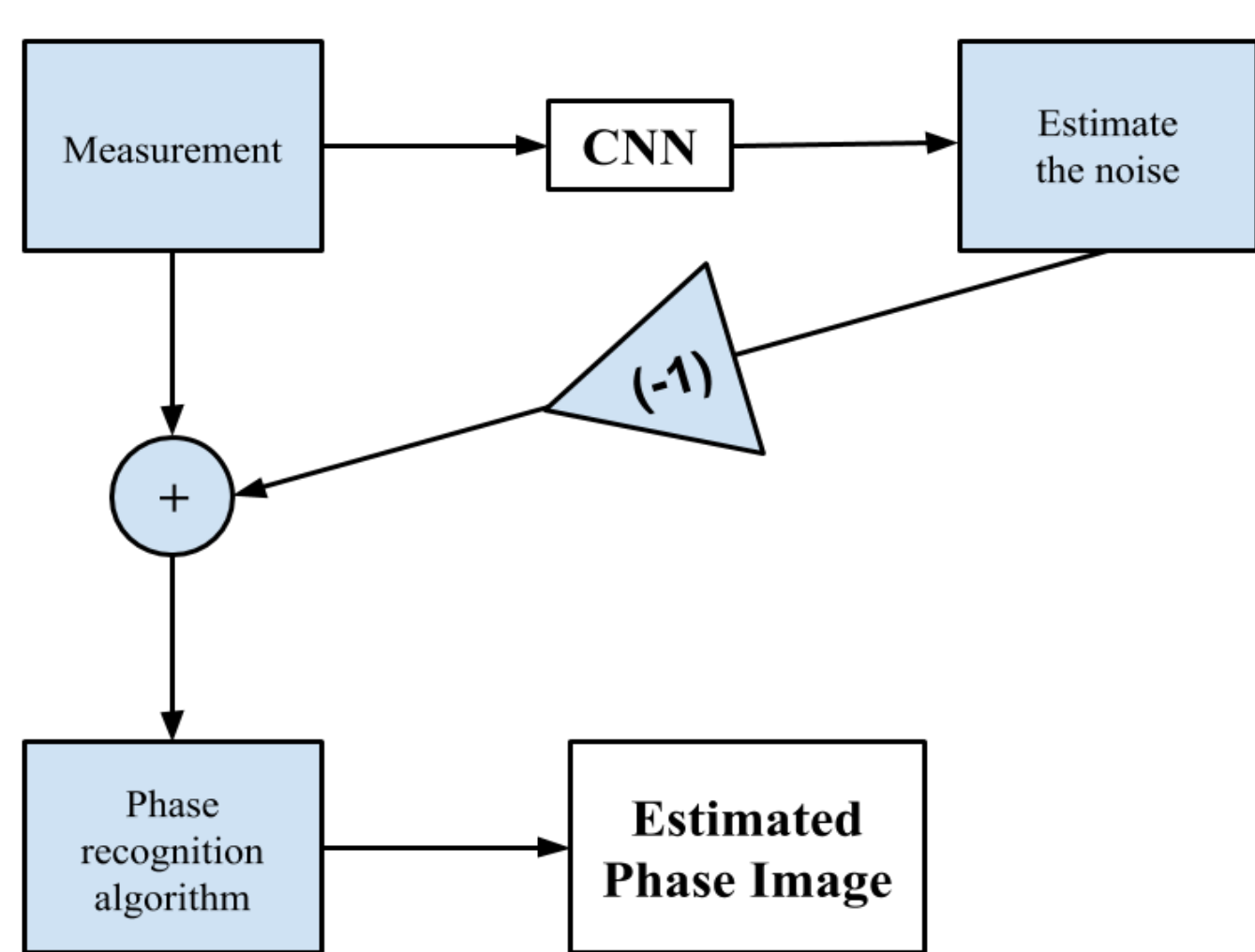


Figure 2. Algorithm of the proposed method.

- **Proposed method:** Remove noise prior to inversion of the measurement by using an implementation of the machine learning framework TensorFlow

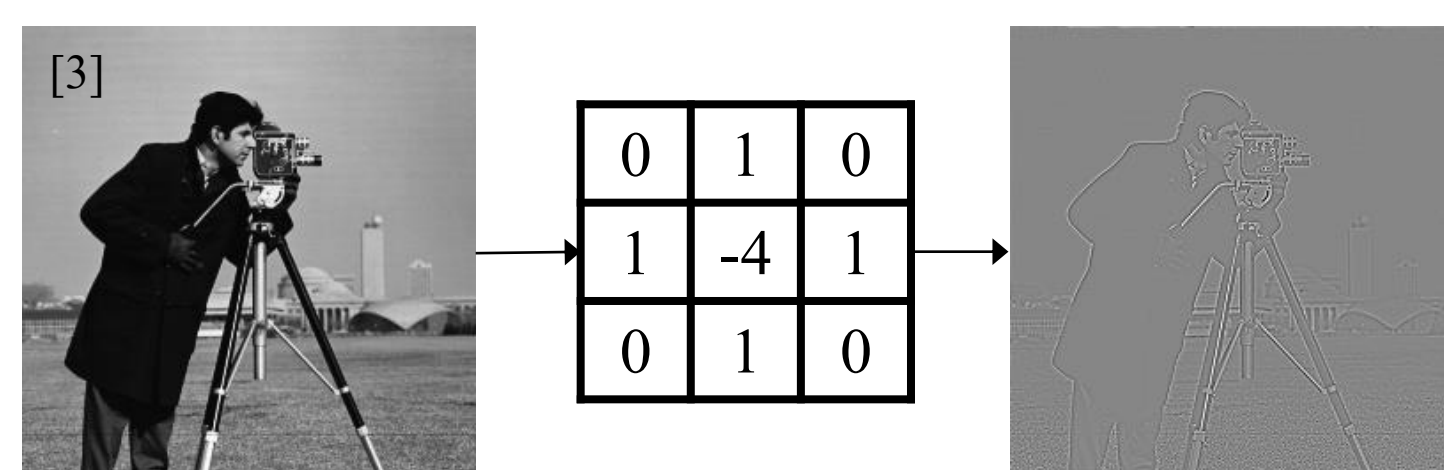


Figure 3. Apply Laplacian to reduce image sensitivity to noise.

$$L(x, y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}$$

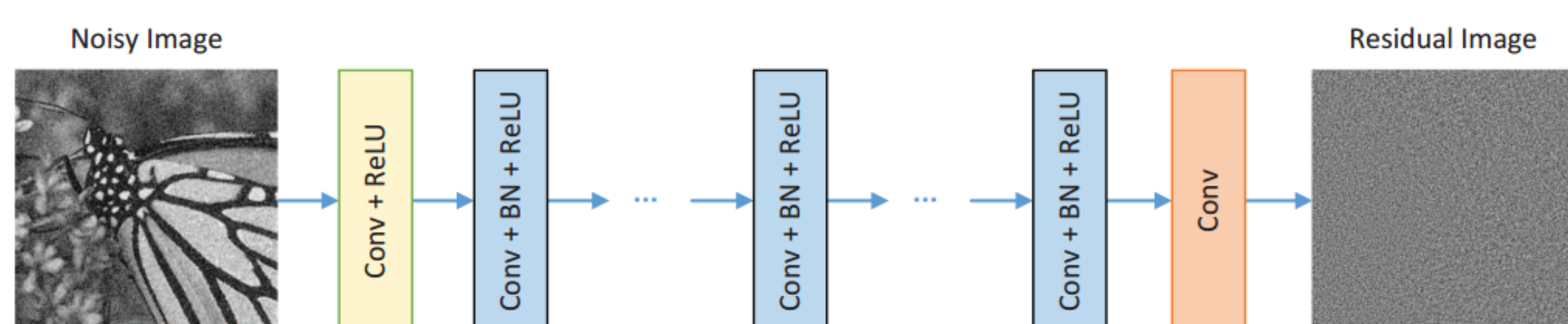


Figure 4. Model of the algorithm CNN [3].

## Denoising Analysis

SNR of the Noisy Image	SNR of the Denoised Image
28.4994	33.0437
25.8447	30.2158
27.6516	31.2802

### In Figure 5:

- Difference in SNR between noisy image and the image denoised by using a proposed algorithm is 4-5 dB
- This difference is crucial for the phase images of the cells at the molecular level.

Figure 5. Signal-to-noise ratio (SNR) of the results.

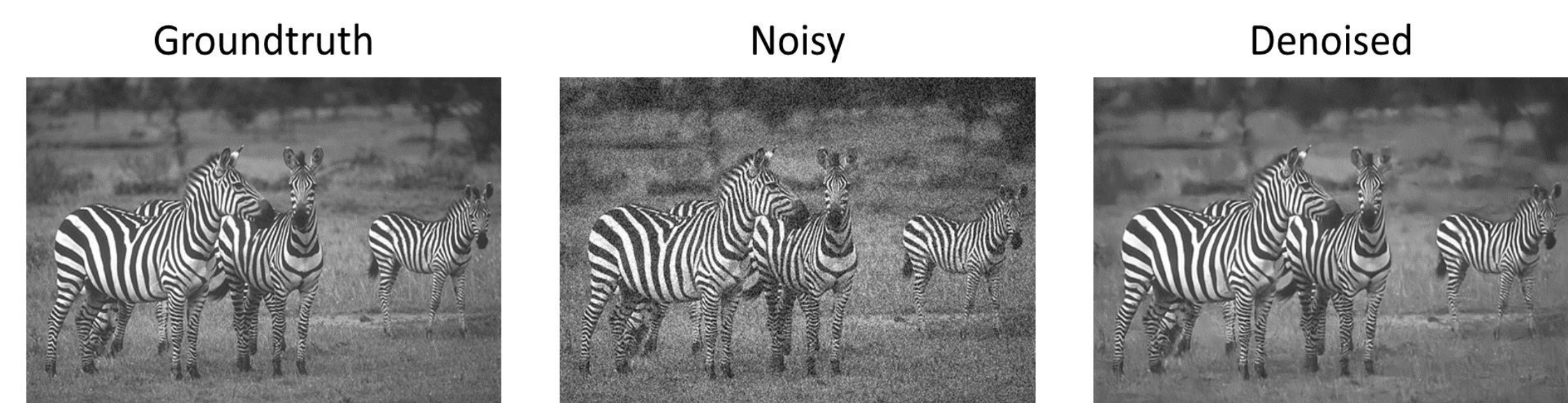


Figure 6. Noise representation: Results compared [3].

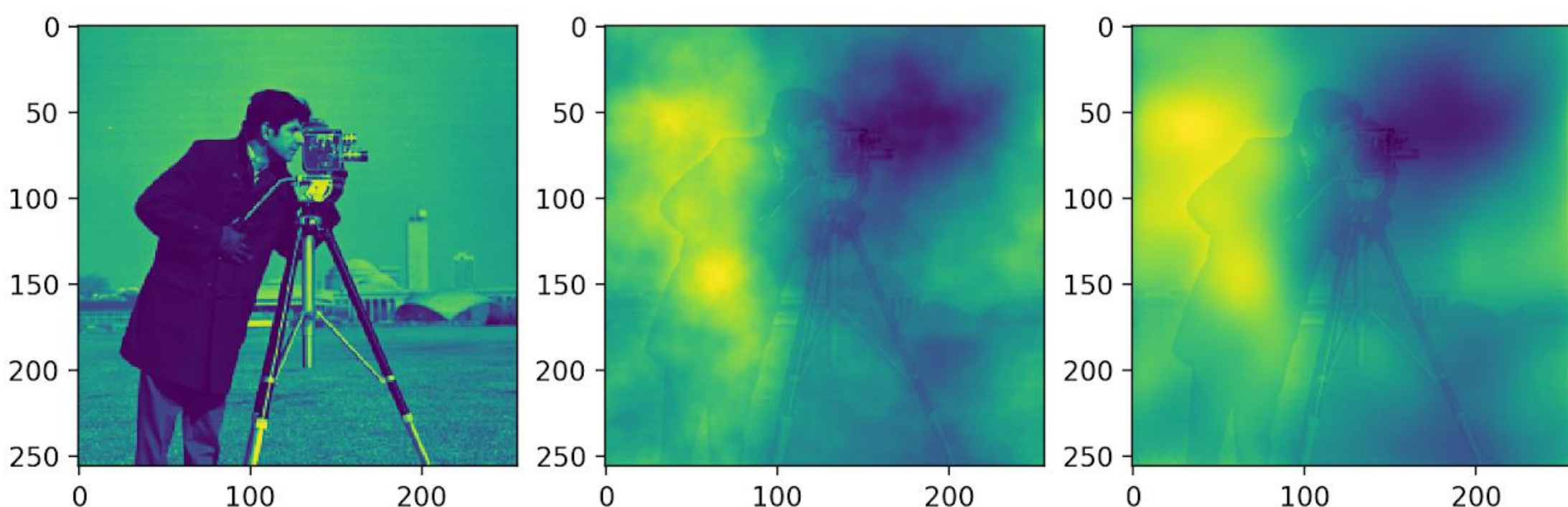


Figure 7. Results when applied Fast Fourier Transform to get the phase reconstruction (Original image on the left, noisy image in the middle, denoised on the right).

### In Figure 7:

- Distinct difference at the level of noise imaged on the level of the phase
- The result seen on the right is a Fast Fourier Transform of the denoised image. All of the details of the original image are clearer in comparison.

## Results

- Introduced a new nonlinear algorithm for the denoising problem in phase imaging
- Approach was based on the Machine Learning technique and TensorFlow framework
- Saw major differences in a final phase image resulting from applying a denoising algorithm
- Using method of the denoising algorithm before phase retrieval algorithm proved to yield better phase images, while also being computationally cheaper
- Illustrated benefits of the proposed method to image analysis by showing the compared images of the phase with noise versus denoised

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## References

- [1] L. Waller, S. Kou, C. Sheppard, and G. Barbastathis, "Phase from chromatic aberrations," *Opt. Express* 18, 22817-22825 (2010).
- [2] E. Bostan, E. Froustey, M. Nilchian, D. Sage and M. Unser, "Variational Phase Imaging Using the Transport-of Intensity Equation," in *IEEE Transactions on Image Processing*, vol. 25, no. 2, pp. 807-817, Feb. 2016. doi: 10.1109/TIP.2015.2509249
- [3] K. Zhang, W. Zuo, Y. Chen, D. Meng and L. Zhang, "Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising," in *IEEE Transactions on Image Processing*, vol. 26, no. 7, pp. 3142-3155, July 2017. doi: 10.1109/TIP.2017.266220

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