Computational interference microscopy (CIM) enabled by deep learning

Original title: Single-shot computational spatial light interference microscopy (SSC-SLIM)

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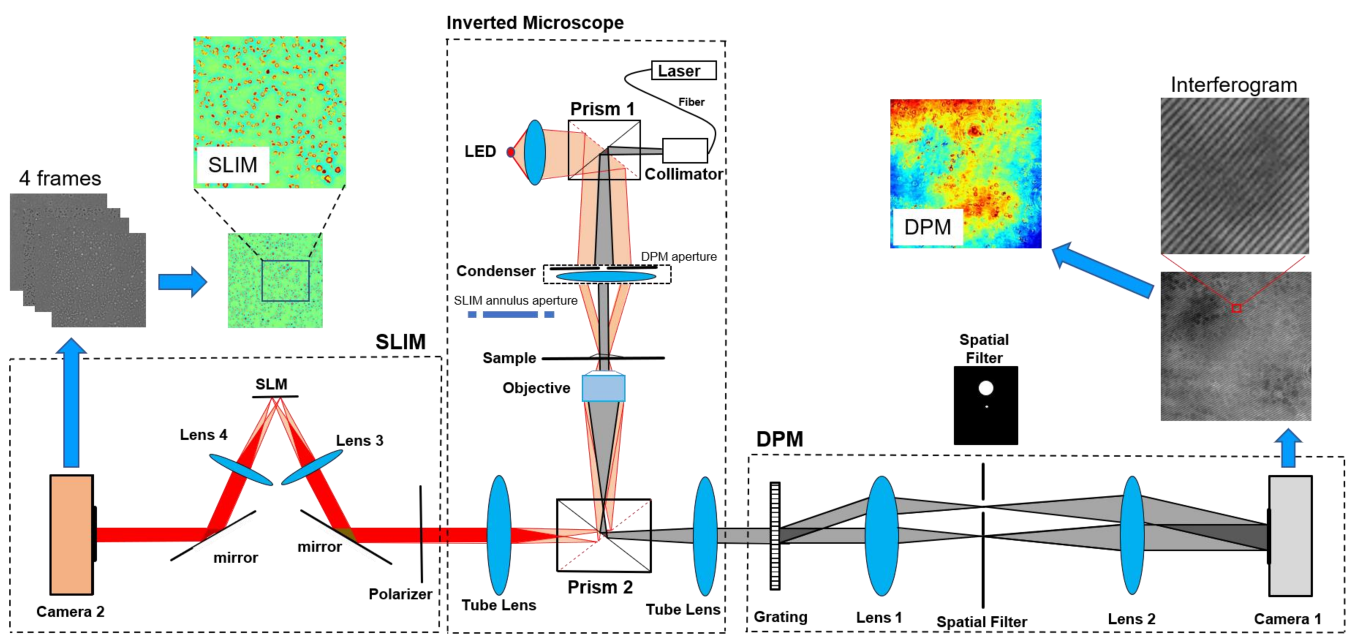
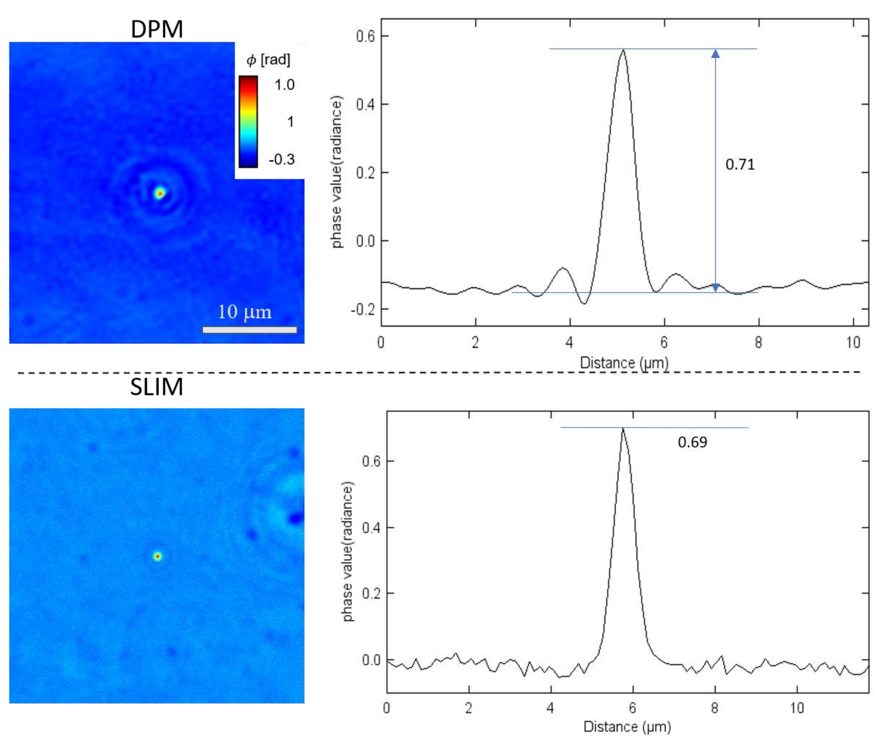
Abstract

Quantitative Phase Imaging (QPI) reveals the phase map of the sample, which has been widely applied in characterizing cells and tissues. Diffraction Phase Microscopy (DPM) as a QPI tool, is proven an efficient method with the advantage of one-shot imaging, while is plagued with speckles and multiple reflections. Spatial light interference microscopy (SLIM) overcomes those defects, however, the capture rate is limited by 4 shots imaging. Now, machine learning has been widely used in field of imaging. Here, we propose an Enhanced DPM by utilizing neural networks that can produce SLIM-quality phase maps from DPM images. Our capture system is built on an inversed microscopy, the right port connects DPM, and the left connects SLIM. By switching the inside prism, we get DPM and SLIM images separately. We constructed a deep learning model based on U-Net and trained on over 1000 pairs of DPM and SLIM images. From the test set results, we observed that the model learned to remove the speckles in DPM, and overcame the background phase change during time. Finally, we applied our model in a live imaging soft, make a video to compare DPM, SLIM and U-net images in real-time, the result indicates our model works well and achieve high-contrast phase map at video rate.

System Setup

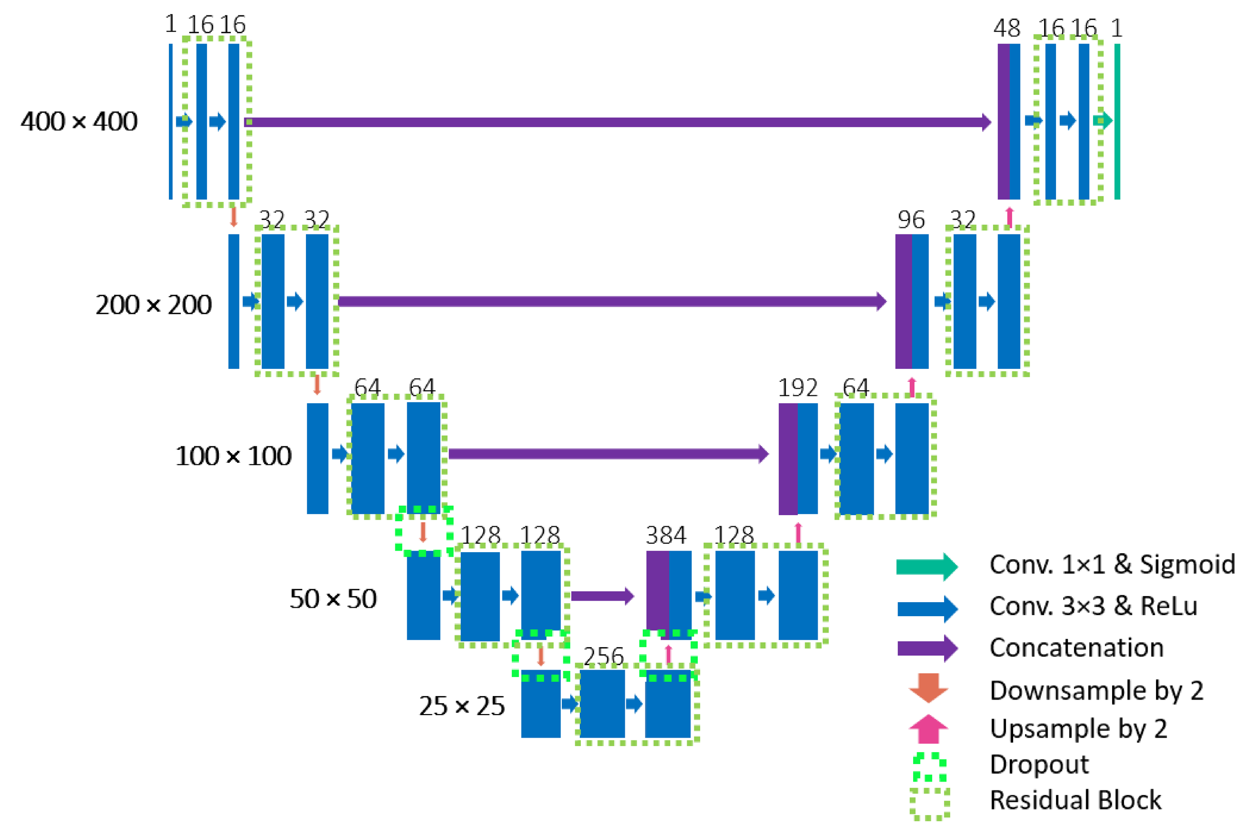


- The system is built around an inverted microscope. The two side ports connect to the DPM (right) and SLIM (left) modules.

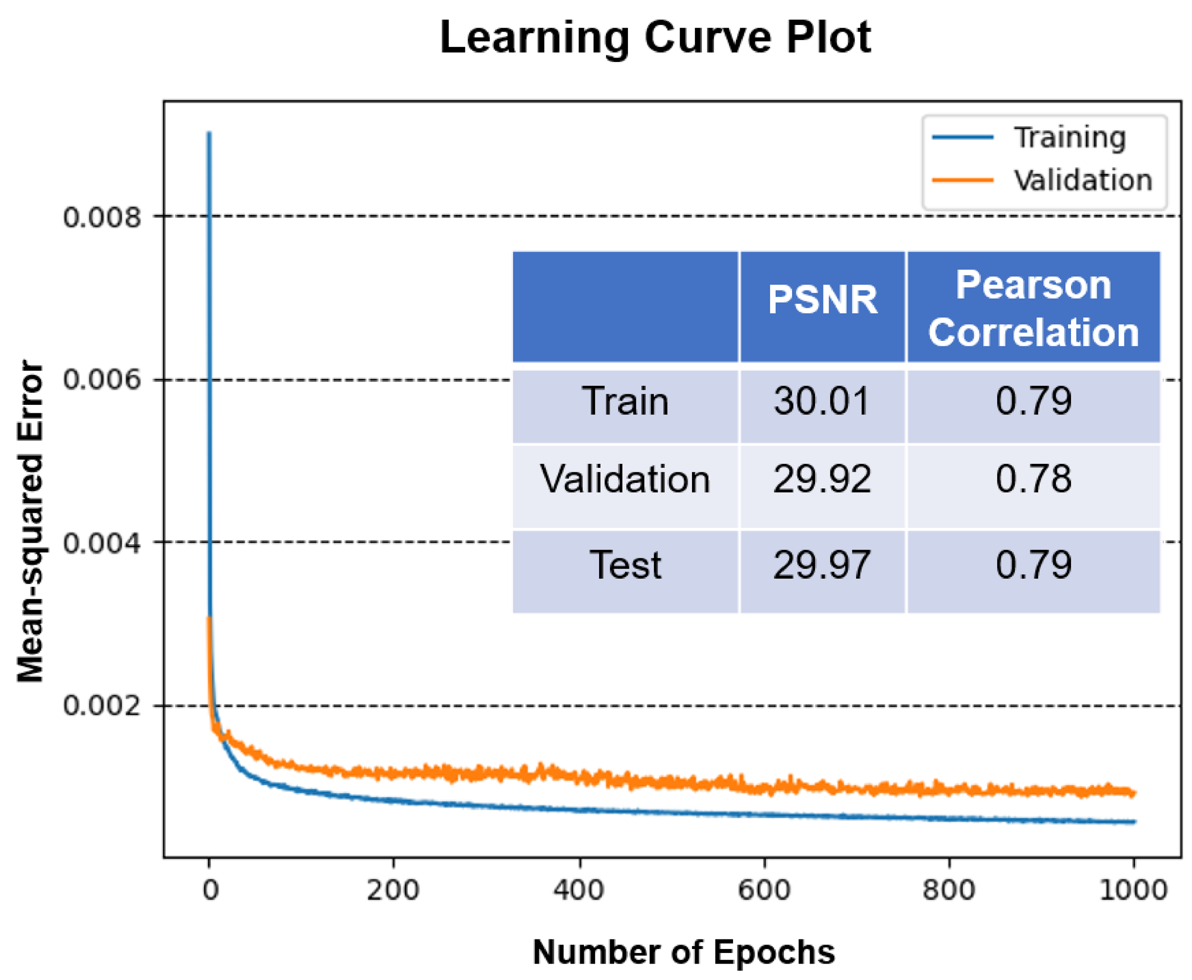


- The measured phase values of the beads using DPM and SLIM are both comparable to the expected number.

Training on red blood cells



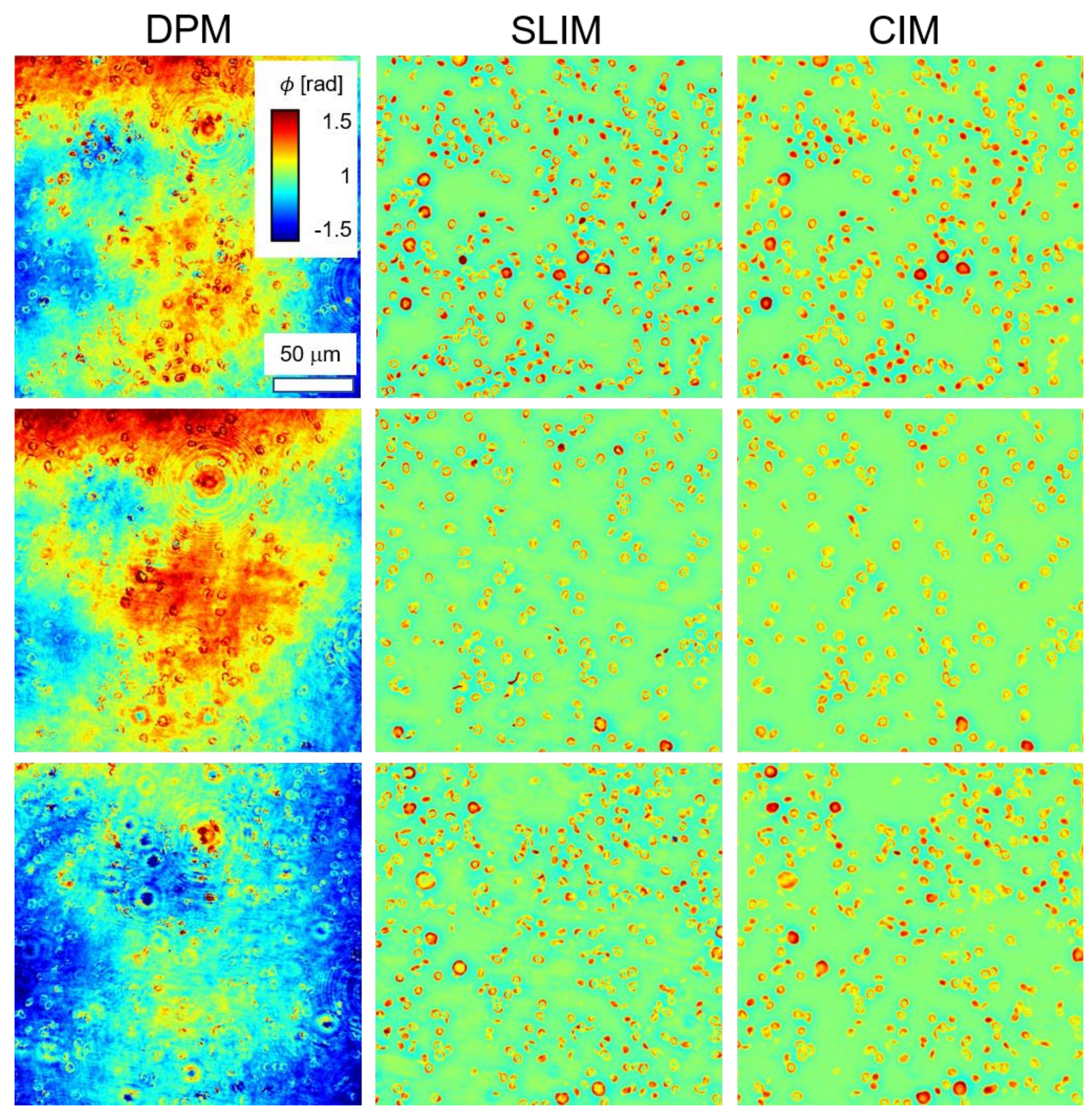
- We picked U-Net as the network architecture.
- We added batch normalization layer, residual connections into the original U-Net architecture. We also reduced the number of filters in the network by a factor of 10.
- During training, we randomly sampled 400 × 400 pixel regions from the DPM images and fed those to the model.
- The model was trained against L2 loss and optimized using the Adam optimizer.



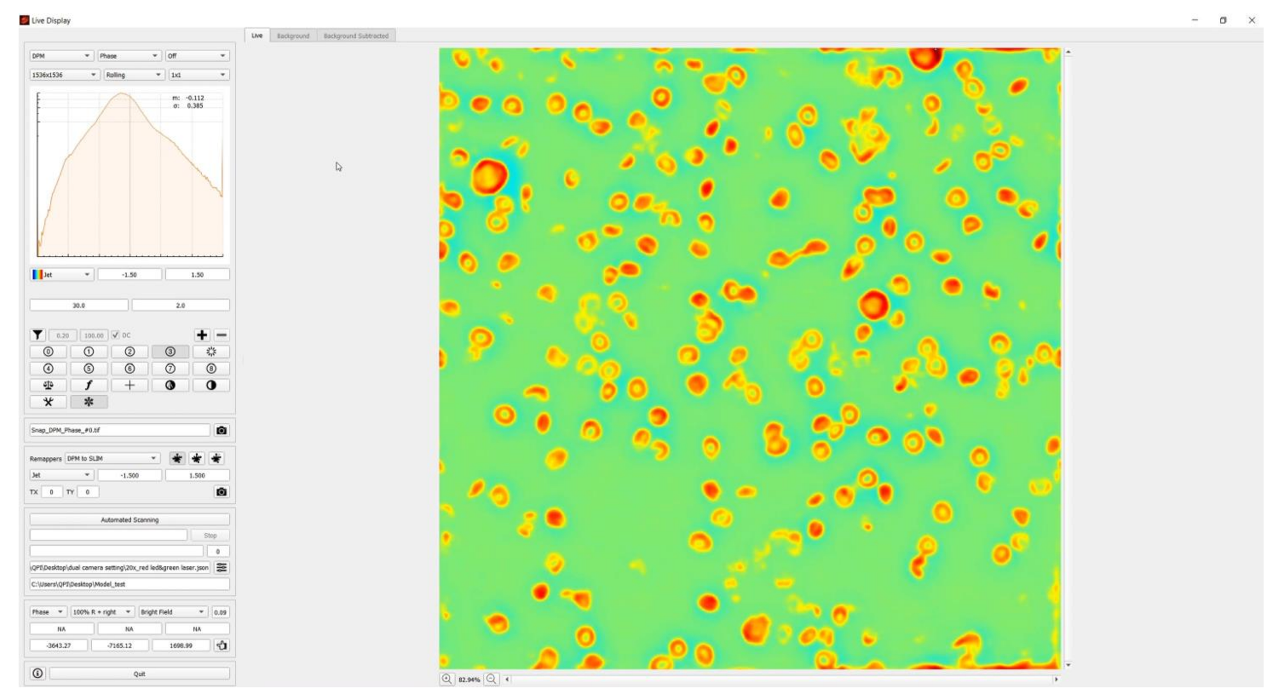
	PSNR	Pearson Correlation
Train	30.01	0.79
Validation	29.92	0.78
Test	29.97	0.79

- The model was trained for 1000 epochs. Within each epoch, the model's weights were updated 270 times.
- The model checkpoint that generated the lowest validation loss (after 800 epochs) were picked as the final model was used for analysis and evaluation.

Results



- The model attained on average 30 PSNR and 0.8 Pearson correlation coefficient on the test dataset.



- The model was ported into our acquisition software for real-time inference.

Reference and Funding

1. G. Popescu, Quantitative phase imaging of cells and tissues, McGraw-Hill biophotonics (McGraw-Hill,New York, 2011).
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3. Y. Jiao, Y. R. He, M. E. Kandel, X. Liu, W. Lu, and G. Popescu, "Computational interference microscopy enabled by deep learning," arXiv preprint arXiv:2012.10239, 2020.

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