Resolution enhancement of spatial light interference microscopy (SLIM) using deep learning

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INTRODUCTION

One of the major challenges in the field of quantitative phase imaging (QPI) is boosting the resolution beyond the diffraction limit [1]. While being highly sensitive to axial changes in phase [2, 3], QPI images still suffer from blurring by the point spread function (PSF). Enhancing the resolution can be achieved either through hardware by oblique or structured illumination [4-6] or through computation, using deconvolution algorithms and deep learning [7].

In this study, we present a method for increasing the resolution of spatial light interference microscopy (SLIM) [2] images using standard deconvolution algorithm adapted for complex fields input and deep learning. Input SLIM phase images are used to create respective complex fields, which are then deconvolved with the PSF using the Richardson-Lucy algorithm [8, 9]. A U-Net model [10] is then trained on the corresponding SLIM and deconvolved images to produce resolution enhanced images. The motive to introduce deep learning in this framework is to increase the speed of deconvolution, since traditional Richardson-Lucy algorithm is iterative and takes time to process single image. However, with the help of a U-Net trained on deconvolution, the speed of deconvolution increases by a factor of 100 for a set of 1000 images and this model can be implemented in real time, into the acquisition software. Future work entails incorporating different magnification images in the model training.

Computational resolution enhancement of spatial light interference microscopy (SLIM) through deep learning.

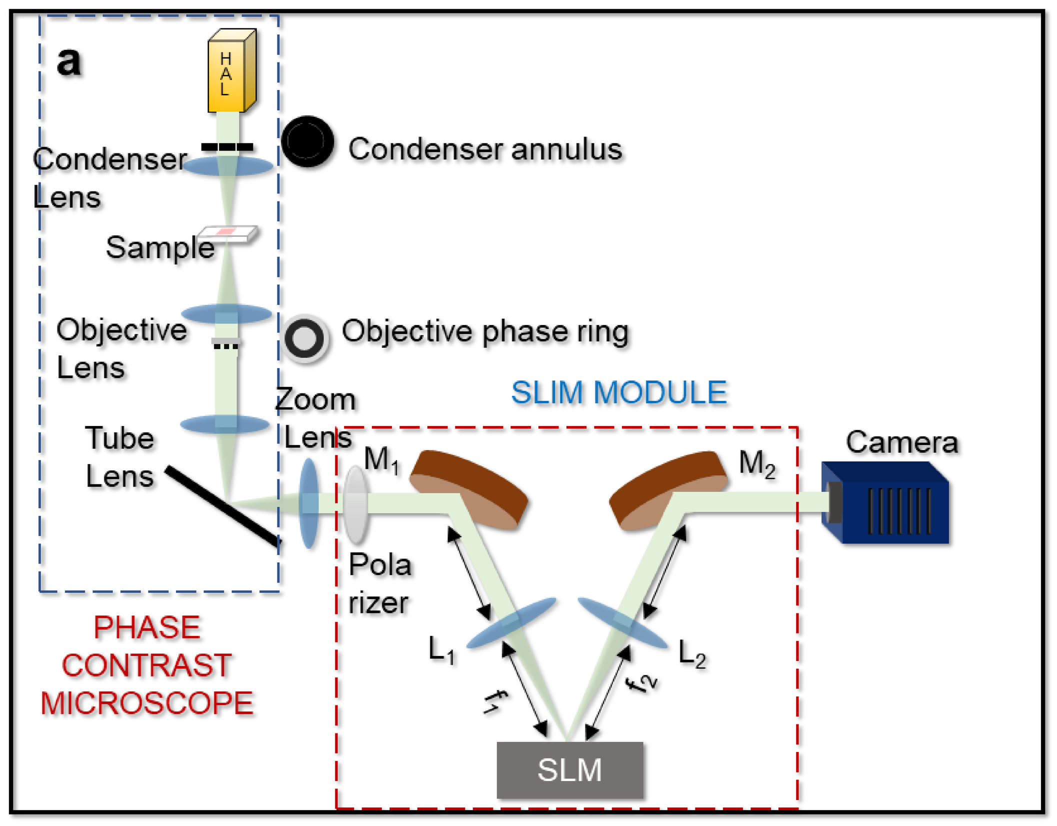

Fig. 1 Spatial light interference microscopy (SLIM). Figure Courtesy. Ref.11

METHODS

To estimate the experimental PSF for a particular objective (40x/0.95 NA in this study), we acquired SLIM images of 100nm polystyrene beads. Using a MATLAB script, images of single beads were cropped from whole field of view image. These psf estimates were averaged to reduce noise and apodised to avoid ringing artifacts. The whole psf extraction procedure is shown in Fig. 2.

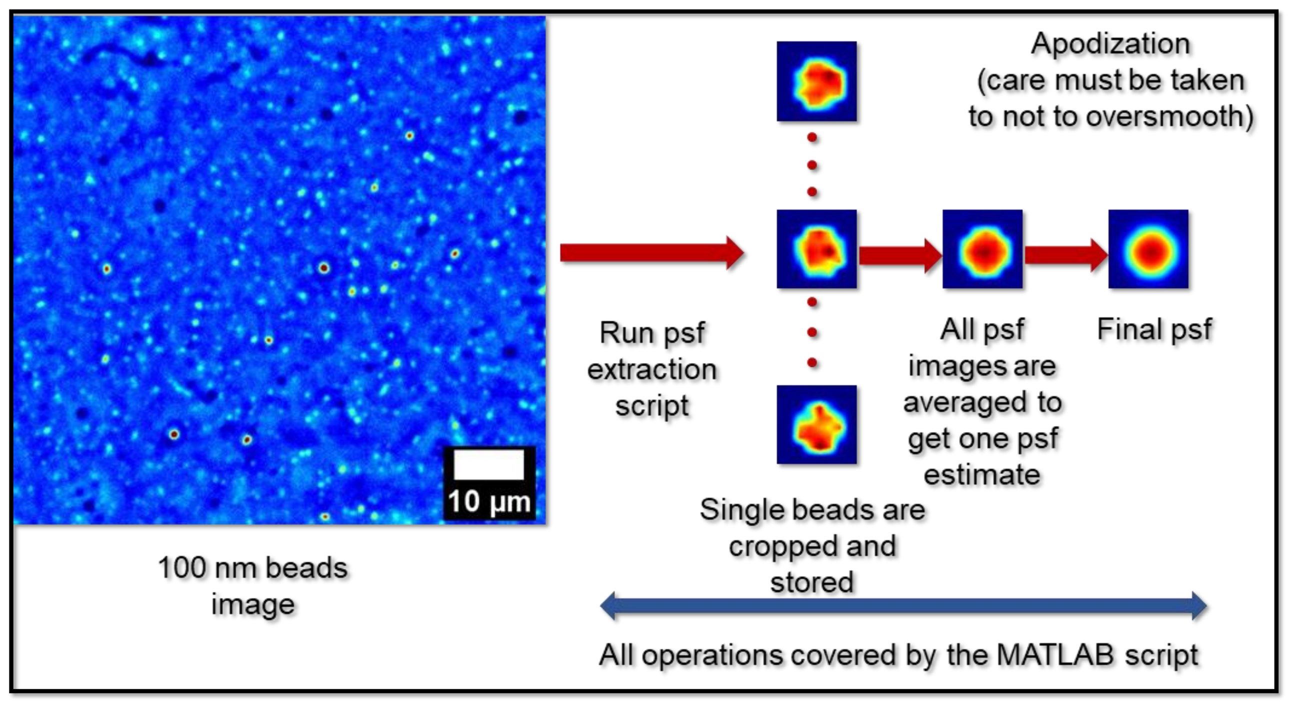

Fig. 2 PSF extraction workflow. Figure Courtesy: Goswami, N et.al (in preparation).

Ground truth data was prepared using Richardson-Lucy algorithm modified for complex field images through MATLAB. Pair of SLIM and deconvolved SLIM images were then used to train a deep learning model (Unet with Efficientnetb0 encoder) as shown in Fig. 3.

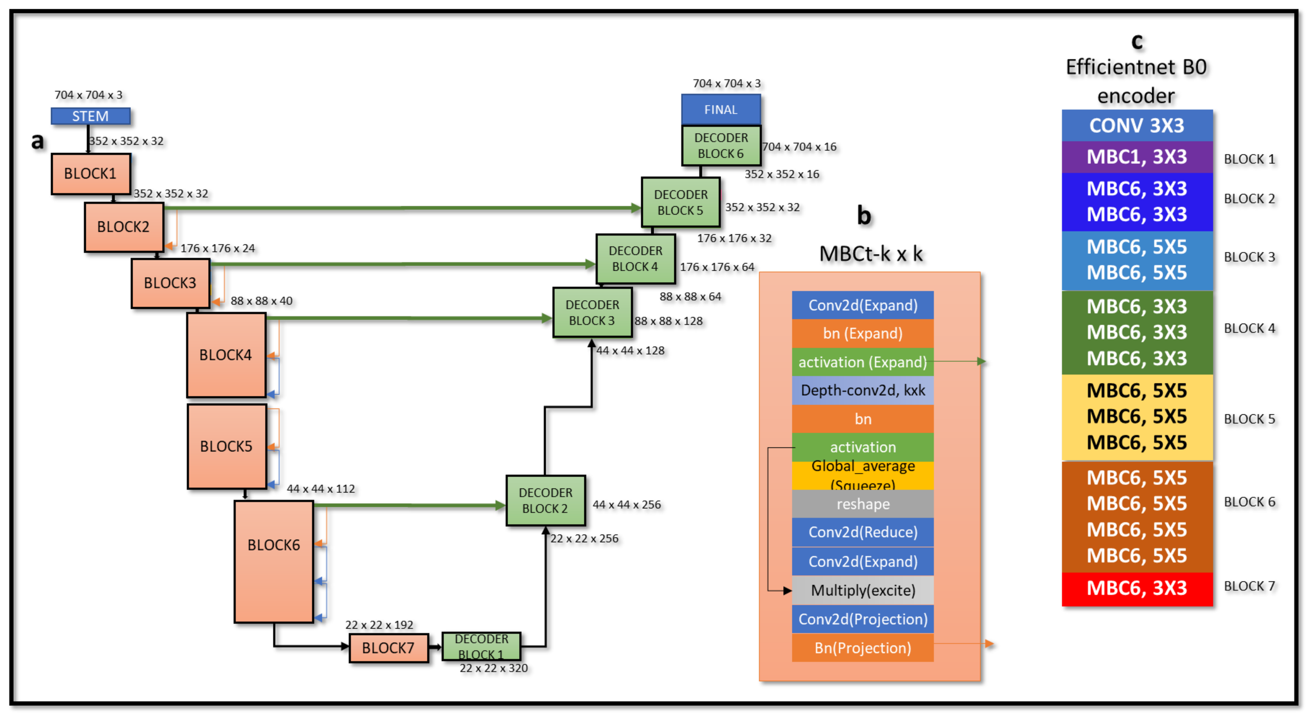

Fig. 3 Model architecture: Unet with efficientnetB0 encoder

Estimates of experimental psf were obtained from SLIM images of 100nm polystyrene beads and output of modified Richardson-Lucy deconvolution algorithm was used as a ground truth to train deep learning model.

RESULTS

The model predictions are shown in figure 4, where it can be seen that the model can deconvolve the SLIM images and enhance the resolution of the raw SLIM image successfully.

The model attained high metrics: SSIM 0.99, PSNR 51.0 and PCC 0.95 indicating that it can successfully reproduce deconvolution results without explicit knowledge of psf. This process is 100 times faster than conventional processing of 1000 images.

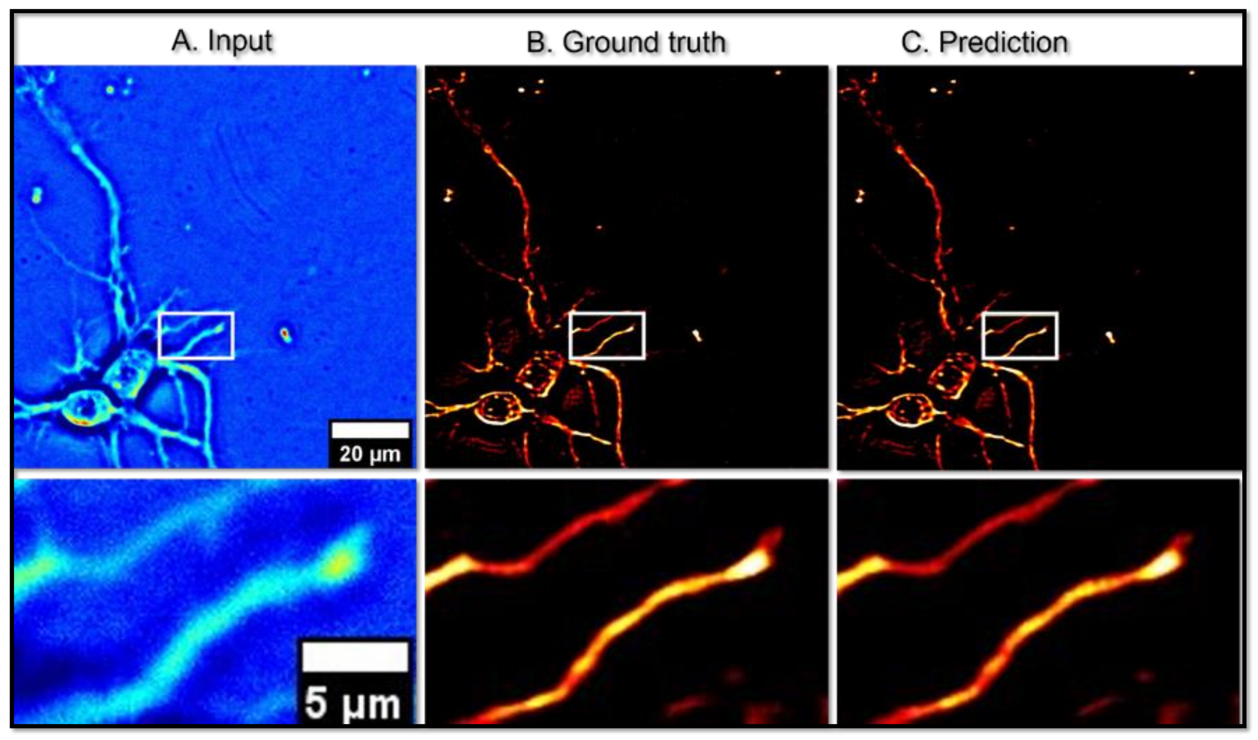

Fig. 4 Model predictions

CONCLUSIONS

1. **Richardson-Lucy deconvolution algorithm with TV regularization was modified was complex images and used to produce ground truth data.**
2. **The deep learning model was successful in resolution enhancement of the raw SLIM images with a gain in speed of 100 for 1000 images.**

This method can be incorporated into real time acquisition.

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