MultiWienerNet: A Learning-based Shift Variant Reconstruction Algorithm

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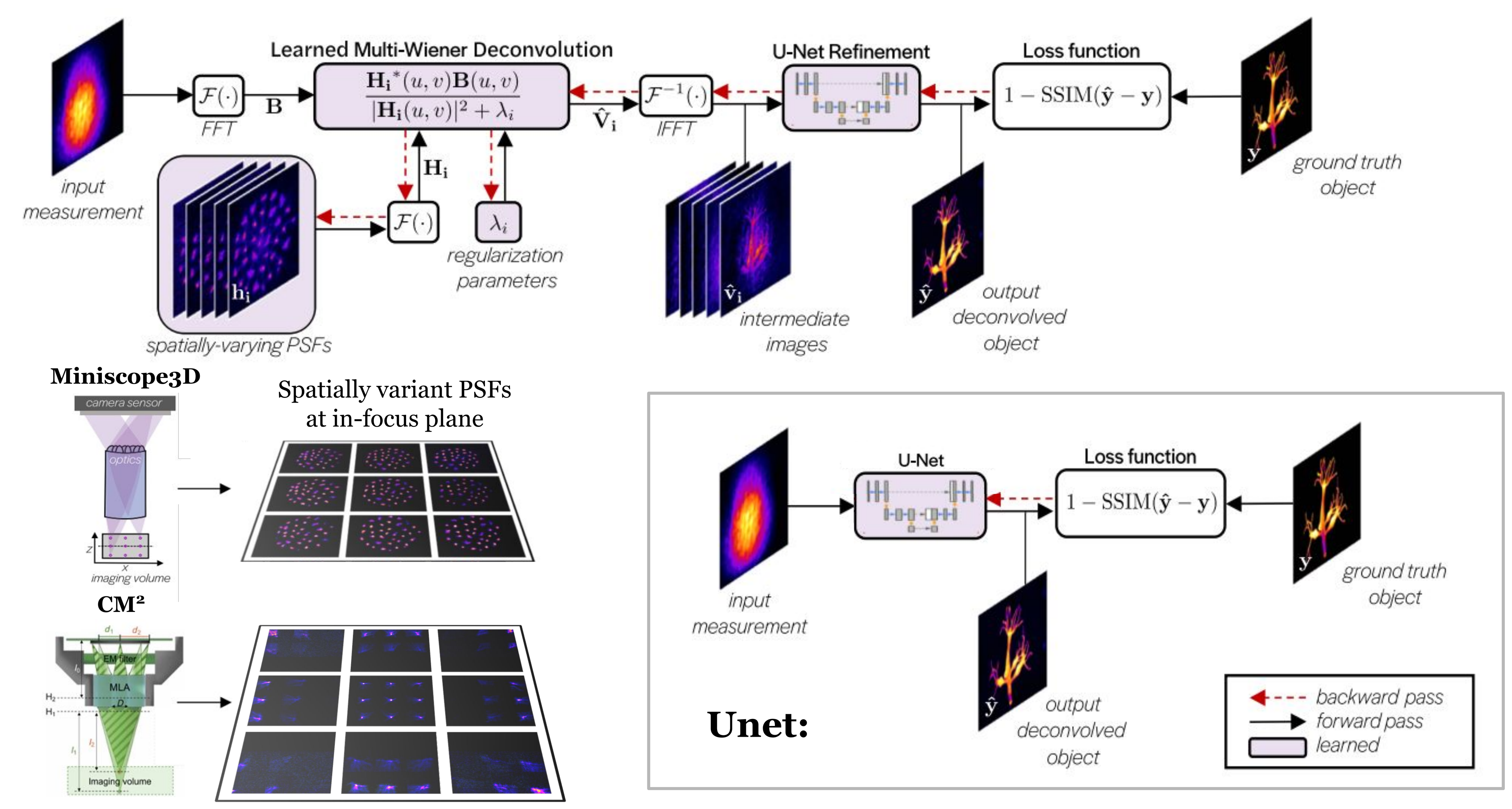
Introduction

Computational microscopy is emerging as a powerful tool in the imaging field that breaks the limitations of traditional microscopy by jointly designing the optics and algorithms. A critical step for these techniques is compressively encoding the object and deriving a reconstruction algorithm to recover the object from the multiplexed measurement. By far, most model-based reconstruction algorithms assume shift-invariance, which means that the point spread functions (PSFs) are the same everywhere in the field-of-view (FOV). However, the space invariance is only approximately valid under very restrictive assumptions, and neglecting this aspect can significantly degrade the reconstruction quality. Traditional shift variant deconvolution requires fully calibrated point spread functions (PSFs) and searches iteratively for optimal solutions, which is both physically laborious and computationally expensive. In this work, I used a deep-learning model known as MultiWienerNet to address this problem for various computational microscopes.

Methods

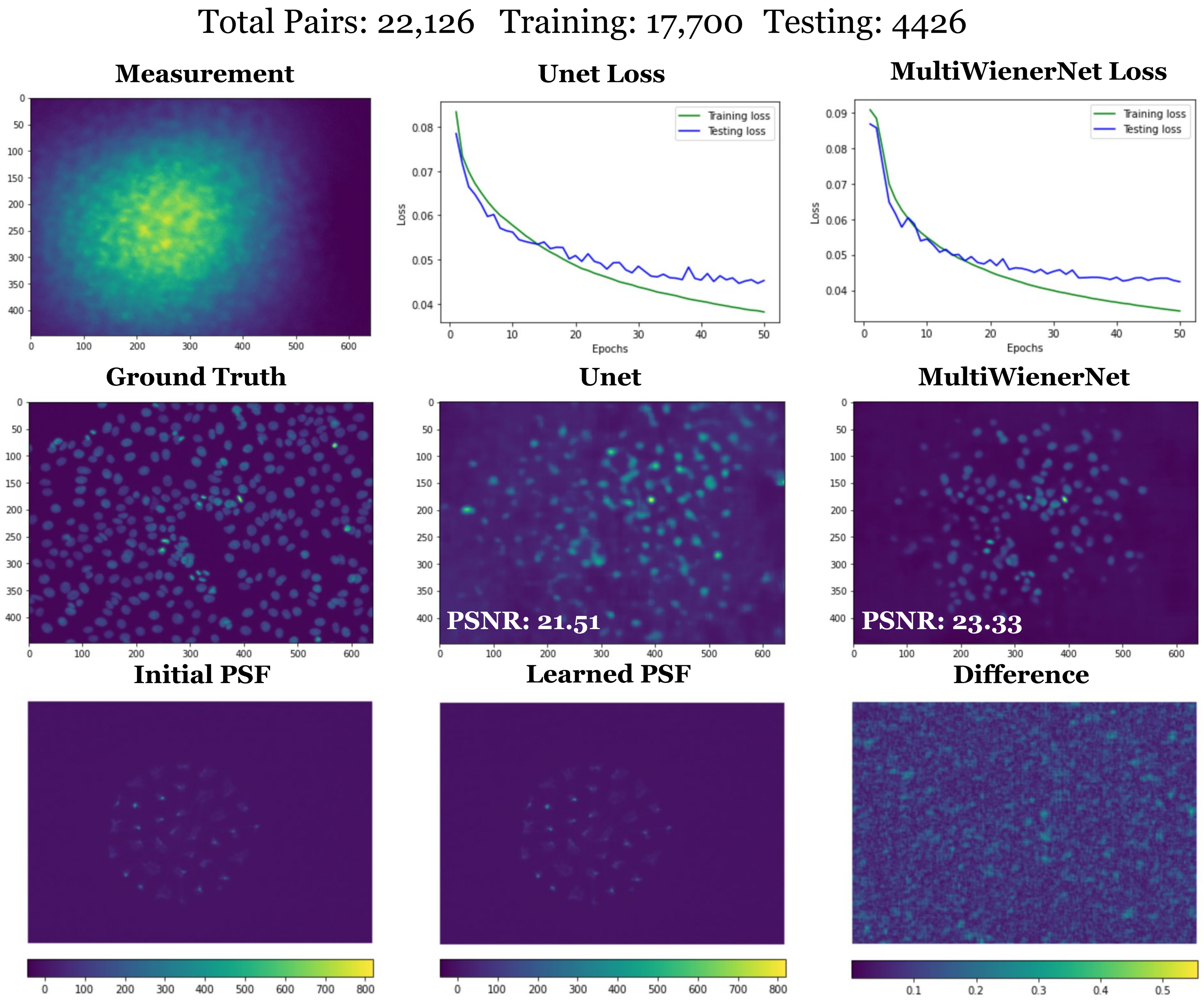
MultiWienerNet:



Results

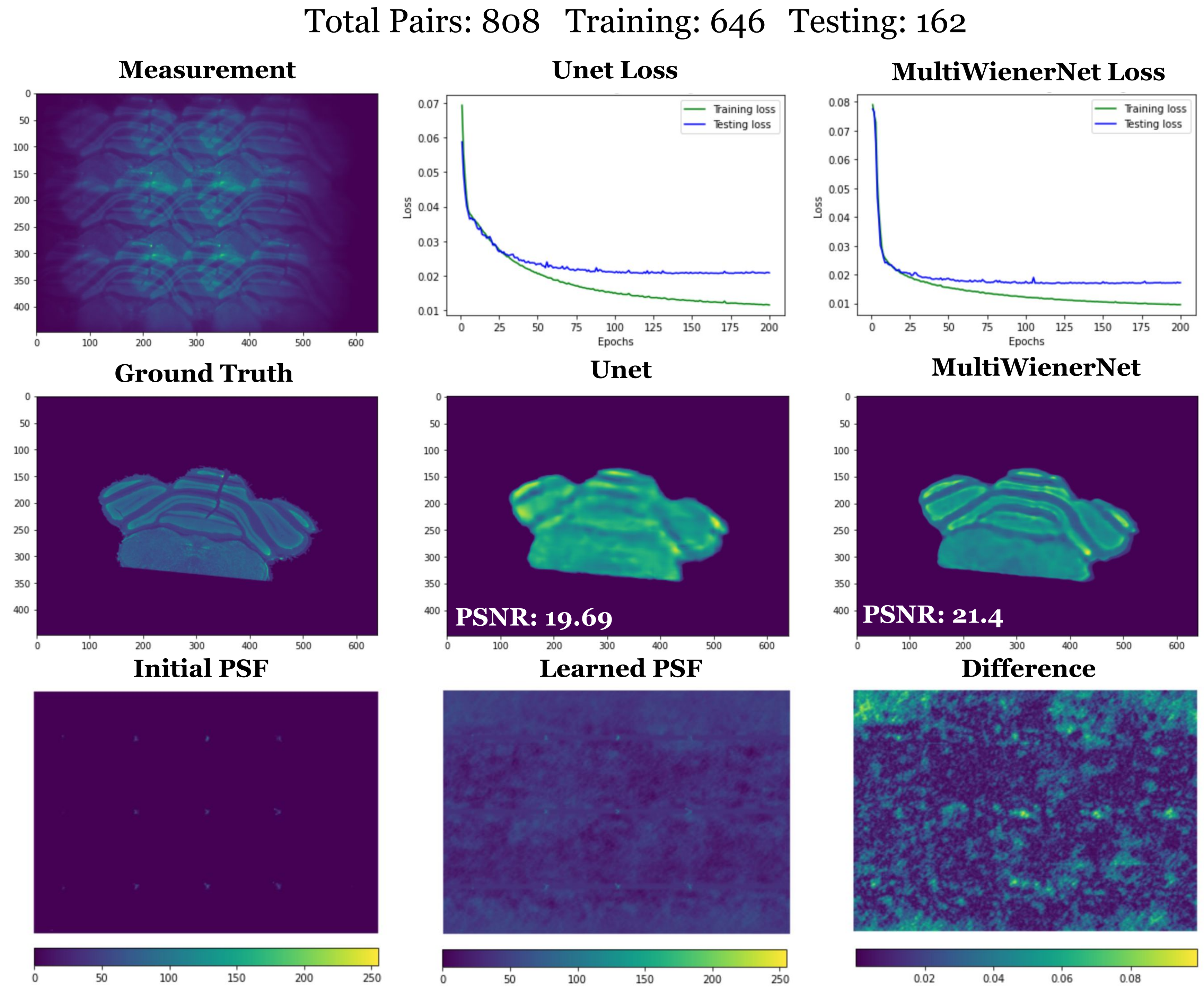
Miniscope3D

Total Pairs: 22,126   Training: 17,700   Testing: 4426



CM²

Total Pairs: 808   Training: 646   Testing: 162



Discussion

In this study, a recently developed deconvolution network, termed MultiWienerNet, is explored to account for shift variance aberrations for two types of computational microscopes (Miniscope3D and CM²). To demonstrate the effectiveness of the MultiWienerNet, I compare the deconvolution results on the testing dataset with a vanilla U-Net that is trained by the same datasets and training schemes. First, I show for both the Miniscope3D and CM² dataset, the MultiWienerNet converges to a lower loss than the Unet within a shorter time. Moreover, the reconstruction results from the MultiWienerNet achieves a better peak signal-to-noise ratio (PSNR) and provides more high frequency details with an enhanced image quality. This is because the learned PSFs incorporate the spatial variance information from the dataset during training process (shown in PSFs difference map). In summary, my results show that by utilizing spatially-varying information, the MultiWienerNet can perform robust reconstructions and outperforms existing deep-learning-based methods like Unet.

References

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