Wide field-of-view imaging with hyperbolic metalenses using a Restormer network

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1. Introduction

Metasurfaces, particularly metalenses, have revolutionized optics by enabling ultra-thin, multi-functional components that outperform traditional bulky lenses. Metalenses achieve this by manipulating light at the nanoscale, enabling the replication of complex phase profiles while maintaining a compact form factor. This unique capability makes them highly valuable for applications in imaging, sensing, and optical metrology [1, 2]. Among metalens designs, those with a hyperbolic phase profile stand out for their exceptional on-axis focusing efficiency and diffraction-limited performance [3]. However, their utility in imaging is hindered by significant off-axis aberrations, which restrict the field-of-view (FOV) and limit practical applications [4].

These aberrations result in images with spatially varying blur artifacts that cannot be deblurred using traditional approaches such as Wiener filtering. Iterative algorithms for spatially varying deconvolution have been developed [5], but these methods are slow, sensitive to calibrations, and unable to remove noise [6]. Recent efforts have shifted toward deep-learning algorithms to correct spatially varying aberrations [7, 8, 9, 10, 11, 12, 13, 14, 15, 16]. However, training these neural networks often requires the time-consuming curation of experimental datasets and is prone to overfitting to specific imaging conditions (lighting, field-of-view, etc.).

In this work, we present a neural network-enabled, reference-free hyperbolic metalens camera capable of wide FOV imaging. By employing a Restormer neural network [17] trained on simulated datasets using the eigen-point-spread function (eigenPSF) method [5], we eliminate the need for experimental data curation and ensure robustness across varying imaging conditions. Our approach achieves aberration-free imaging over a 54° FOV, demonstrating exceptional performance in both low-light and close-up imaging scenarios. This work bridges the gap between hardware limitations and software solutions, paving the way for practical, high-performance metalens-based imaging systems.

2. Results

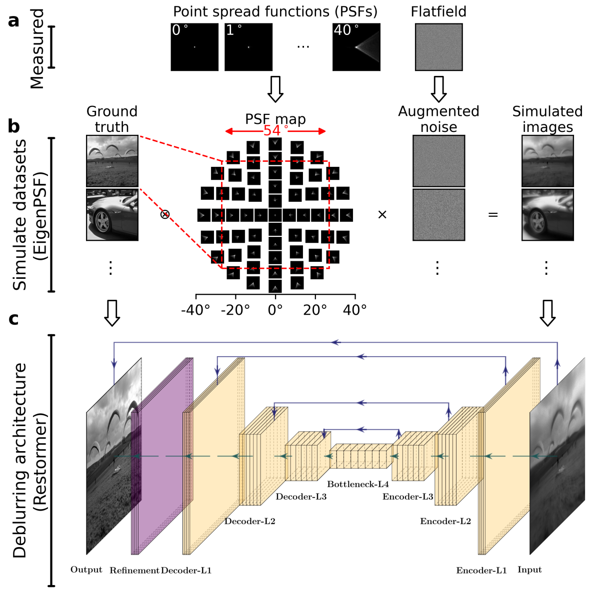

Fig. 1: Schematic for computational deblurring using the Restormer architecture trained on eigenPSF-simulated images.

Fig. 1 shows the schematic of our computational deblurring approach for hyperbolic metalens imaging. To properly characterize the image formation model, we first measured the PSFs of our hyperbolic metalens camera at different angles of incidence (AOI) ranging from 0° to 40° (Fig. 1a). These imaging PSFs are computationally rotated to populate a PSF map that covers the full extent of an image corresponding to an angular FOV of 54° as shown in Fig. 1b. The eigenPSF method uses this PSF map to simulate spatially varying blur applied to ground truth images from Google's Open Images dataset [18, 19]. Each simulated blurred image is corrupted with noise by augmenting a measured flatfield through random rotations and flips. A Restormer network is then trained using these 3500 simulated images as input, and their corresponding ground truth images as the desired output (Fig. 1c).

Fig. 2a,c shows the raw measurements from our

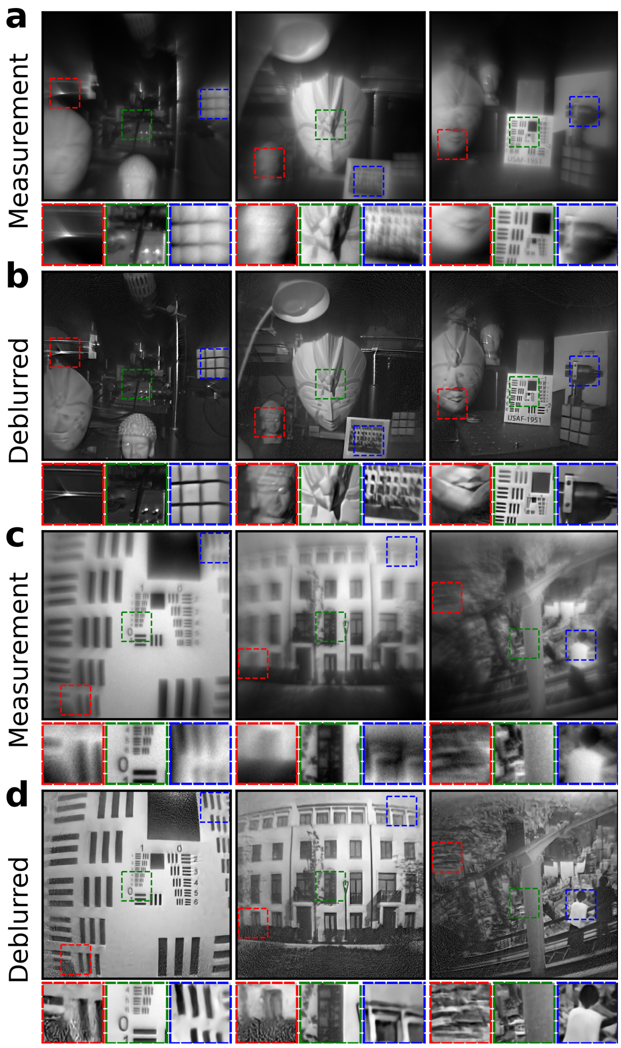

Fig. 2: Deblurring images from the hyperbolic metalens camera using the trained, reference-free Restormer network. The (a) measured and (b) deblurred images of scenes taken around a lab. The (c) measured and (d) deblurred images of printed photos placed before the camera. All images have the same angular FOV of $54°$.

hyperbolic metalens camera and the corresponding results of Restormer deblurring on the images. The characteristic aberrations due to the hyperbolic lens phase profile are evident in the sharp features at the center of the image and the increasing coma at larger incidence angles. Despite spatially varying aberrations in the measurements, the trained Restormer network is able to deblur the full FOV of the images in real-time ($\sim$50 ms per image), recovering features even toward the edges of the images. By using a reference-free dataset, we avoid overfitting to specific imaging conditions during the training of the Restormer network. This is evident in the similar quality of deblurring from both measurements of lab scenes (dimmer) and printed photos (brighter) in Fig. 2b,d.

Our findings suggest that the field of view (FOV) in hyperbolic metalens imaging could be further extended by leveraging advances in computational power to train on larger image sizes. Additionally, the diffraction-limited resolution of the hyperbolic lens along the optical axis remains underutilized due to current limitations in detector pixel sizes and the large bandwidth of the illumination source. With future improvements in hardware, this work has the potential to open new pathways toward achieving high-resolution, wide-FOV imaging with hyperbolic metalenses.

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