Lensless Scanning Super-resolved Imaging of Arbitrary Shaped Objects

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We build super-resolution images of arbitrary shaped and sized objects pixel-by-pixel via deep learning-enabled analysis of their light scattering patterns. First proof-of-principle experiments show resolution better that $\lambda/4$.

The Abbe-Rayleigh diffraction limit presents a long-standing challenge in microscopy, limiting the resolution of conventional microscopes to ~$\lambda/2$. Typically, this limit is overcome by invasive means, e.g., by the introduction of fluorescent labels or by near-field scanning. Here, we introduce a novel scanning microscopy approach that allows imaging beyond the diffraction limit in a conventional microscope by neural network processing of scattering patterns from the imaging target.

Our approach is based on scanning of the imaging target with a tightly focused illumination field and processing the corresponding diffraction patterns by a convolutional neural network (CNN). We train our neural network on diffraction patterns simulated from a set of square arrangements of 3x3 fully opaque or transparent pixels (hereinafter called superpixels), surrounded by three rows of random black and white pixels. We used a large dataset of 12,288 diffraction patterns from different superpixels with different surroundings. The size of the superpixel is so that a focused Gaussian beam with the wavelength λ = 640 nm and the waist of 600 nm (0.94λ) fully covers it. The training process flow is shown in Fig. 1a. Then we numerically simulate scanning of the object (here it is a Siemens star in an otherwise opaque screen) with the same Gaussian laser beam. The resulting diffraction patterns are recorded at a distance of two wavelengths away from the object (see Fig. 1b). The recorded patterns, corresponding to different relative positions of the sample and optical focus, are then analyzed by a CNN, which subsequently allows to reconstruct the object (Fig. 1c).

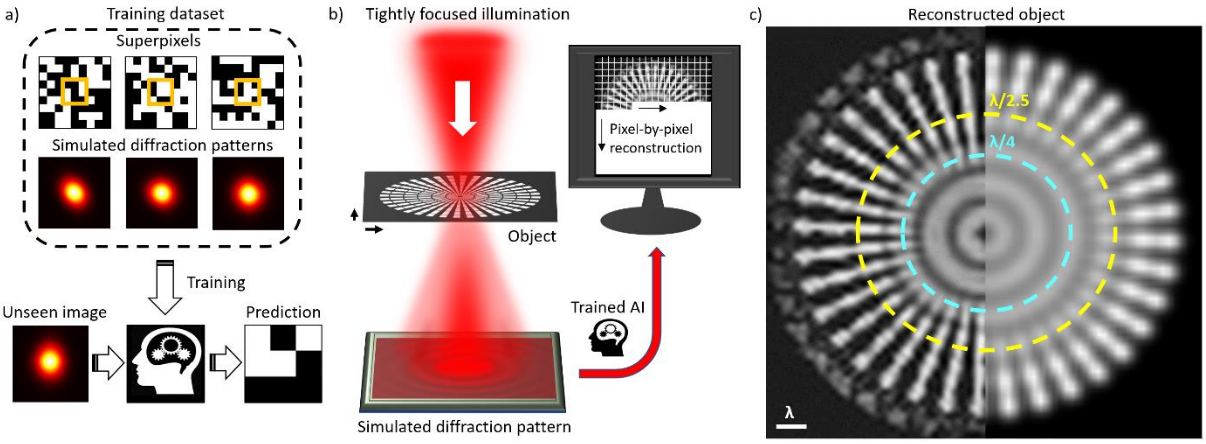

Fig. 1 (a) Neural network training process flow. The neural network is trained on diffraction patterns from 3x3 square arrangements of fully opaque or transparent pixels (superpixels), surrounded by three rows of random opaque or transparent pixels. The trained neural network predicts the superpixel from an unseen diffraction pattern.; (b) Artistic impression of the method. The 2D object is scanned by tightly focused light. Diffraction patterns, recorded at the distance of 2λ away from the object are fed into the pre-trained convolutional neural network, which reconstructs the object.; (c) Reconstructed image of a Siemens star consisting of 72 black and white fringes using our method (left) and standard confocal imaging (right). The cyan line indicates the location of the smallest resolvable fringes using our method. The yellow line indicates the resolution of standard confocal microscopy.

Imaging resolution is assessed by evaluating the contrast between adjacent white fringes of the reconstructed Siemens star (Fig. 1c). In the present case, this contrast remains large enough to resolve the fringes down to a size of one fourth of the wavelength (dashed cyan circle in Fig. 1c). For comparison, standard confocal imaging is limited to a resolution of $\lambda/2.5$ (dashed yellow circle in Fig. 1c). This high resolution can be attributed to the aptitude of a trained neural network to solve the (otherwise intractable) inverse scattering problem.

We further report on the use of superoscillatory light fields in this AI-assisted imaging regime, where advantage is gained form the presence of phase singularities and high local intensity gradients and wavevectors in the incident field, yielding more complex scattering patterns more sensitive to smaller features of the object, whereby resolution can be extended towards $\lambda/10$.