

Single-shot pixel super-resolution lensless in-line holographic microscopy using object support constraints

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Digital lensless in-line holographic microscopy (DLIHM) enables compact, low-cost, wide field-of-view (FoV) quantitative phase imaging, but its resolution is often limited by the detector pixel pitch because high-frequency holographic fringes are undersampled. We present support-constrained aliasing-reduction pixel super-resolution (SCAR-PSR), a single-shot reconstruction framework that explicitly trades FoV for resolution gain by enforcing a known finite object support. SCAR-PSR recovers the phase with sub-pixel resolution from a single, highly under-sampled diffraction intensity measurement. Using a calibrated USAF 1951 target image, the proposed method provides stable phase recovery, demonstrating a $\sim 5\times$ resolution gain relative to the native sensor sampling. We further evaluate robustness under realistic detector constraints through photon-limited Poisson noise, bit-depth quantization, and convergence stability studies. These numerical results suggest a hardware-minimal route to motion-free, single-shot super-resolution in DLIHM, with potential applicability to high-speed imaging scenarios involving rapidly evolving phase objects. © 2026 Optica Publishing Group. All rights, including for text and data mining (TDM), Artificial Intelligence (AI) training, and similar technologies, are reserved.

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1. INTRODUCTION

Originating from the fundamental work of Gabor on wave-front reconstruction and the early development of digital hologram recording and reconstruction [1–3], DLIHM has emerged as a compact and cost-effective computational imaging modality that leverages scalar diffraction theory to reconstruct the complex optical field of a specimen without the requirement of imaging lenses. This lens-free system configuration of DLIHM exhibits a wide FoV equal to the active area of the charge-coupled device (CCD)/complementary metal-oxide-semiconductor (CMOS) image sensor with sub-micron resolution, enabling label-free and quantitative phase imaging for diverse applications in biology, medicine, and environmental monitoring [4–9]. By utilizing an on-chip geometry where the object is placed close to the image sensor, the DLIHM system operates at a high geometrical numerical aperture (NA) and unit magnification [6]. However, this unit-magnification geometry introduces a severe, fundamental restriction on the resolving power of the system. Due to the finite pixel pitch of the image sensor, spatial frequencies in the diffraction pattern above the Nyquist frequency are severely undersampled [10–12]. This results in aliasing artifacts and prevents the system from achieving its theoretical diffraction-limited resolution. Thus, the ultimate spatial resolution achievable in this modality is

predominantly restricted by the finite pixel pitch of the discrete detector array rather than by the diffraction limit.

To overcome pixel-limited resolution and approach the coherent diffraction limit ($\lambda/2$) [10], pixel super-resolution (PSR) techniques are fundamentally required [6,9,10,12]. To achieve this, hybrid hardware-computational approaches have been widely explored. Conventional PSR methods rely on multi-frame, measurement diversity achieved through temporal multiplexing, wherein multiple intensity frames are sequentially recorded and computationally fused. To obtain multiple holograms, additional optical/mechanical components can be used. The most widely used approach is multi-frame fusion [13], which involves acquiring several subpixel-shifted intensity measurements and combining them to synthesize a higher spatial sampling grid. Experimentally, this is realized through controlled lateral shifts of the illumination aperture, object, or the sensor array, thereby increasing the effective spatial sampling density [14]. This process effectively provides a high-resolution hologram that enables high-resolution image reconstruction [14].

Beyond lateral-shift-based PSR, other multi-measurement strategies include recording multiple axially shifted holograms (defocus diversity and multi-height phase retrieval) [9,15], sweeping the illumination wavelength across a broad spectrum

(multi-wavelength diversity) [16,17], or varying the illumination angle [14]. However, these multi-frame PSR methods suffer from alignment sensitivity and require precise subpixel registration [18] and accurate knowledge of axial distances. To mitigate the severe alignment sensitivities inherent in these methods, joint optimization frameworks have been introduced to simultaneously estimate the high-resolution object field alongside the unknown recording parameters, such as lateral displacements, sample-to-sensor axial distances, and illumination tilts [19,20]. Furthermore, coded illumination and sensing form another important class of strategies increase diversity and information content in the measurement. Structured light-emitting diode (LED) or spatial light modulators (SLMs) patterns can modulate (heterodyne) high spatial frequencies into the pass-band, thereby improving conditioning [21,22], while coded sensors that incorporate thin random modulation layers directly at the detector plane can encode otherwise poorly transferred components, enabling improved phase recovery in multi-height settings [23]. While these multi-frame measurement strategies successfully achieve PSR, they fundamentally compromise the temporal resolution of the imaging system. Furthermore, multi-measurement frameworks necessitate intricate optomechanical hardware, such as precision motorized stages or programmable SLMs, and demand rigorous, computationally expensive subpixel image registration to avert severe reconstruction artifacts. These limitations make multi-frame PSR methods unsuitable for high-speed imaging of rapid dynamic biological phenomena or for their application in low-resource settings.

To achieve single-shot phase recovery with improved resolution, data-driven approaches leveraging deep learning techniques have recently been proposed as a rapidly growing paradigm [24–27]. These architectures can be broadly categorized into two classes. Purely data-driven methods implicitly learn an inverse mapping from a single aliased intensity measurement directly to a high-resolution complex optical field. Despite achieving rapid inference speeds, they lack mathematical convergence, physical guarantees for phase uniqueness, and domain generalization. To improve reliability, multi-prior and physics-informed neural networks (PINNs) integrate measurement models and physical constraints directly into the architecture [28]. While PINNs enhance noise robustness and empirical stability, they still lack strict deterministic guarantees of convergence and phase uniqueness, and they present reproducibility concerns [19,24,29,30]. Consequently, deterministic constraint-driven approaches—including finite support [31], sparsity, and total variation (TV) regularization—provide stabilized phase recovery and, in some cases, enable hologram self-extrapolation beyond the measured aperture [32–34]. In addition to inverse-problem-based reconstruction methods, several image preprocessing and post-processing techniques, such as histogram normalization, background subtraction [4,35], and denoising methods including nonlocal filtering and transform-domain approaches (e.g., BM3D), have also been used to improve holograms prior to reconstruction or to enhance reconstructed image quality, particularly under noisy acquisition conditions [36]. While these methods can suppress noise and improve visual quality, they generally cannot recover physically lost information caused by detector undersampling in the same deterministic sense as PSR reconstruction methods.

In summary, multi-frame diversity methods achieve robust resolution gains but at the cost of acquisition complexity; coded single-shot methods increase throughput but often require specialized hardware; and prior-based algorithms reduce data requirements but rely on assumptions that may not hold true for different classes of samples [8,37]. Nevertheless, existing approaches do not fully resolve the problem of achieving motion-free, single-shot PSR in DLIHM.

Conversely, deterministic constraint-driven methods such as finite support [31], sparsity, and TV regularization, formulate phase retrieval as a mathematically rigorous inverse problem. By enforcing strict physical priors, these iterative techniques recover the lost phase and missing high-frequency information from a single intensity measurement, thereby providing stabilized phase recovery and enabling hologram self-extrapolation beyond the measured aperture [32–34]. Despite having potential to provide PSR, constraint-driven approaches [6,38] are less explored for single-shot PSR and have primarily limited to twin-image-free image reconstruction [31,39]. Most prior phase retrieval and holographic reconstruction algorithms that use support constraints for image reconstruction from single-shot intensity measurement, mathematically assume an idealized point-like continuous detector or pointwise discrete sampling, thus introducing a severe forward model mismatch that intrinsically limits the fidelity of high-frequency wavefield recovery and limits the deterministic reconstruction of spatial frequencies beyond the native sensor pixel pitch.

In this paper, we propose SCAR-PSR, a deterministic, single-shot framework designed to overcome the resolution limitations of DLIHM, imposed by the finite sampling pitch of the image sensor without using any mechanical scanning, complex optomechanical hardware, or extensive training data. Leveraging the fundamental principle that the Fourier transform of a spatially bounded object constitutes an entire analytic function, we demonstrate that a high-resolution, complex-valued optical field can be uniquely reconstructed from highly aliased, undersampled diffraction intensity measurements by rigorously incorporating a discrete pixel-binning operator into the forward imaging model. The SCAR-PSR framework explicitly trades field of view (FoV) for subpixel resolution gain by enforcing a known, finite object support constraint, which drastically increases the measurement-to-unknown ratio to stabilize the numerical inversion. Mathematically, this reconstruction is implemented as a variational inverse problem that embeds a discrete pixel-binning operator directly into the physical forward imaging model and couples an exact downsampled data-fidelity term with a TV regularization penalty [40]. Solved via the fast iterative shrinkage-thresholding algorithm (FISTA) [41,42] to ensure accelerated convergence, our framework is validated through comprehensive simulations using complex-valued pure phase objects and calibrated USAF resolution charts. The results demonstrate a $\sim 5\times$ resolution gain relative to native sensor sampling and robust performance under severe Poisson noise and bit-depth quantization.

The main contributions of this work are as follows: (i) the demonstration of single-shot PSR in DLIHM using restricted-support priors and the effect of finite pixel size through the explicit modeling by pixel binning, surpassing native pixel-pitch resolution without mechanical scanning; (ii) a quantitative

evaluation of SCAR-PSR performance using the signal-to-noise ratio (SNR), Pearson correlation coefficient (PCC), and structural similarity index measure (SSIM); (iii) to demonstrate phase recovery with PSR, yielding a resolution gain of around $\sim 5\times$ using calibrated USAF chart image; (iv) we also demonstrated that the developed framework is robust under Poisson noise and bit-depth quantization effects, which are important to include to study its feasibility in realistic experimental conditions; and (v) we also provided convergence studies exhibiting stable reconstruction.

This theoretical foundation and simulation results, together establish the SCAR-PSR as a practical strategy for resolution enhancement in DLIHM for applications, where FoV can be sacrificed. The proposed scheme exhibits high-resolution and also bridges the classical finite-support priors with modern computational super-resolution approach, in a simple and single-shot framework. Subsequent sections of this paper are organized as follows: Section 2 establishes the theoretical background of DLIHM, a pixel-aware forward model, and the theoretical basis for SCAR-PSR method. Section 3 formulates the regularized inverse problem, details of the FISTA-based reconstruction algorithm, and reconstruction procedure. Section 4 outlines the simulation parameters and the quantitative evaluation metrics used. Section 5 presents a comprehensive discussion of our numerical results, including resolution assessments, validation to binary and non-binary (natural) objects, and noise robustness and bit-depth quantization effects, followed by the Section 6 on conclusion.

2. THEORY AND FORWARD MODEL

The schematic of a DLIHM system is shown in Fig. 1. A monochromatic spatially coherent plane wave of wavelength λ illuminates the specimen at the object plane ($z = 0$). The complex amplitude transmission function of the object can be written as

$$O(x, y) = A(x, y) e^{i\phi(x, y)}, \quad (1)$$

where $A(x, y)$ and $\phi(x, y)$ denote the object amplitude and phase, respectively. In our case, we have used a finite support limited object, where support $S(x, y)$ is represented by a binary support function:

$$S(x, y) = \begin{cases} 1, & (x, y) \in \Omega \\ 0, & (x, y) \notin \Omega \end{cases}, \quad (2)$$

where $\Omega \subset \mathbb{R}^2$ denotes the physically admissible object region. The effective exit field just after specimen is written as

$$O_s(x, y) = O(x, y) S(x, y). \quad (3)$$

Using scalar diffraction theory, the field propagated from the object plane $z = 0$ to a sensor located at $z = z$ is given as

$$U_z(x, y) = \mathcal{P}_z\{O_s(x, y)\}, \quad (4)$$

where $\mathcal{P}_z$ is free space propagation for scalar field, which can be numerically modeled using angular spectrum propagation method. This is continuous domain representation of the electric field available for recording. However, the optoelectronic

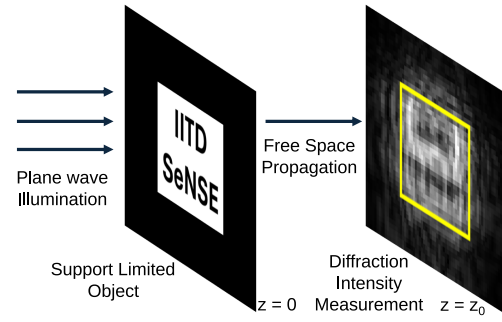


Fig. 1. Schematic of DLIHM setup. A monochromatic plane wave illuminate the object sample and we record diffraction intensity measurements at the sensor plane ($z = z$). This recorded diffraction intensity I_z is used for complex amplitude image reconstruction.

sensor responds strictly to the time-averaged intensity. The continuous diffracted intensity distribution at recording plane is given by

$$I_z(x, y) = |U_z(x, y)|^2. \quad (5)$$

In practice, the sensor does not observe $I_z(x, y)$ pointwise; it records pixel-integrated and sampled values. We account for this explicitly in the next subsection, which motivates the binning-based pixel-aware forward model used in Eq. (8).

A. Discretization on a Pixelated Sensor

In practice, a CMOS/CCD array detector does not perform pointwise sampling of the continuous intensity $I_z(x, y)$. Instead, it samples $I_z(x, y)$ on a discrete Cartesian grid with pixel pitch Δp . Each detector element integrates the incident optical intensity over its finite active area Δp^2 , resulting in spatial averaging prior to digitization such that the recorded value at pixel (m, n) is

$$I[m, n] = \frac{1}{\Delta p^2} \int_{m\Delta p}^{(m+1)\Delta p} \int_{n\Delta p}^{(n+1)\Delta p} I_z(x, y) dx dy. \quad (6)$$

This spatial integration over finite pixel area acts as a low-pass filter, and due to discrete sampling, the spatial frequencies exceeding the Nyquist limit $1/(2\Delta p)$ cannot be uniquely represented on the discrete grid and fold into lower-frequency bands, leading to aliasing and resulting in an irreversible loss of high-resolution structural detail in standard back-propagation reconstructions. The measurement process is therefore governed by both finite pixel geometry and discrete sensor sampling, which together impose a hardware-induced band limitation during recording. Thus, even when the coherent diffraction limit permits higher resolution, the effective system resolution is often dominated by the pixel pitch, imposing a sampling-limited resolution $\delta_{\text{pix}} \approx \Delta p$. To accurately and deterministically invert the physical measurement process, the mathematical forward model must explicitly incorporate the physics of finite pixel integration. Consistent with prior studies examining detector sampling and binning effects in digital holography [43], the pixel integration effect can be implemented numerically using a spatial binning operator ($\mathcal{B}_b$). This binning model approximates an ideal detector with

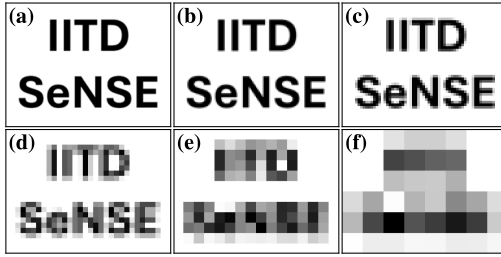


Fig. 2. Illustration of pixel binning in simulations. Starting from the original high-resolution image (a), we show successive downsampling with binning factors $b = 2, 4, 8, 16, 32$ in (b)–(f), respectively.

uniform pixel response and 100% fill factor. Binning with factor b merges non-overlapping $b \times b$ blocks of a fine-grid intensity pattern into single averaged pixel. Explicitly, for a discrete array $A[m, n]$,

$$(\mathcal{B}_b A)[p, q] = \frac{1}{b^2} \sum_{i=0}^{b-1} \sum_{j=0}^{b-1} A[pb + i, qb + j], \quad (7)$$

where p and q index the pixels of the binned (low-resolution) image, and i and j iterate over the high-resolution pixels within each $b \times b$ binning block.

The effect of binning is shown in Fig. 2. Starting from the high-resolution image, successive downsampling with $b = 2, 4, 8, 16, 32$ progressively averages out fine features, emulating detector with coarse pixel size. This discrete operator emulates the physical pixel integration of Eq. (6), while enabling simulations with adjustable effective required pixel size. Accordingly, the diffraction intensity measurements are modeled not as ideal point-sampled measurements, but as downsampled Fresnel diffraction patterns, as can be seen in Fig. 3, in which the physical pixel footprint introduces a deterministic, space-invariant modulation transfer function (MTF) that attenuates high spatial frequencies and must be accounted for during reconstruction.

B. Pixel-Aware Forward Model for a Finite Support Object

Combining angular spectrum propagation, pixel integration, and finite object support, the complete forward model for the binned intensity measurement at distance z of object O is

$$I_z^{(b)} = \mathcal{B}_b \left(|\mathcal{P}_z(O \odot S)|^2 \right), \quad (8)$$

where $\odot$ denotes pointwise multiplication, the object field O and binary support mask S are represented on a discrete fine grid, and $\mathcal{P}_z$ and $\mathcal{B}_b$ are the discrete angular spectrum propagation and binning operators, respectively. Equation (8) makes explicit what the detector actually records: not the ideal point sampled diffraction pattern, but its pixelated measurements. This process is schematically shown in Fig. 3 a finite-support phase object (a) produces a high-resolution hologram (b), whose downsampled versions at $b = 4$ and $b = 16$, shown in Figs. 3(c) and 3(d), respectively, demonstrate progressive loss of fine fringes.

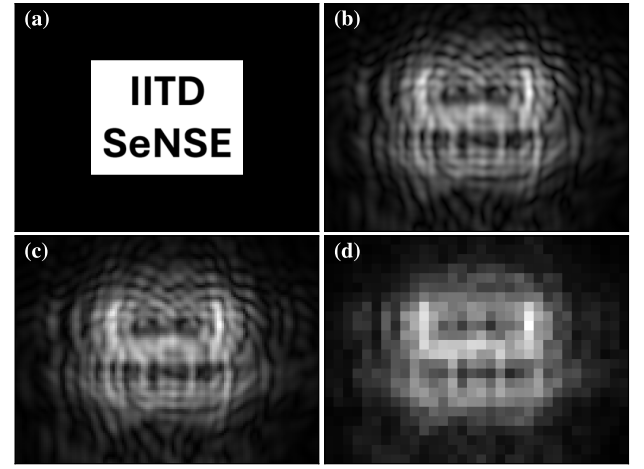


Fig. 3. Illustration of the forward imaging and binning model. A phase object with finite support (a) produces a high-resolution diffraction hologram (b), and corresponding downsampled with binning factors $b = 4$ and 16 , shown in (c) and (d), respectively, show loss of high spatial frequency fringes.

C. Theoretical Basis for Support-Constrained Super-Resolution

If the object $O(x, y)$ has compact support $\Omega \subset \mathbb{R}^2$, its Fourier transform is an entire analytic function. In principle, an entire function can be uniquely determined from its known values over some non-zero region [44]. In DLIHM, the field at the sensor is a Fresnel diffraction pattern, which can be mathematically expressed as the Fourier transform of a generalized object field as the multiplication of the object field by a quadratic phase factor, $O(x, y) \exp[i\frac{\pi}{\lambda z}(x^2 + y^2)]$. Therefore, the principle of analytic continuation also applies to the diffraction patterns of objects with compact support to recover the high-resolution object field from its diffraction intensity measurements. The key observation underlying the proposed framework is that free-space propagation redistributes object spatial frequencies across the measurement domain. A spatially compact object produces a diffraction field whose angular spectrum extends over a broad region of spatial frequencies. Consequently, the high-frequency object information is not lost during propagation but is encoded in the fine-scale interference structure of the recorded hologram. This implies that the full object spectrum is theoretically recoverable from a finite band of measured spatial frequencies.

In practical DLIHM systems, we only have intensity measurement, leading to loss of phase information. Furthermore, the acquisition is also subjected to discrete sampling, finite pixel integration, and optoelectronic noise. Under these realistic conditions, recovery of phase with subpixel resolution is highly ill-conditioned and unstable. Practical recovery therefore requires explicit modeling of detector physics, regularization, and additional constraints to utilize the redundancy in captured information for stability.

The imaging system is discretized in both the object and measurement domains. Let $O \in \mathbb{C}^{N \times N}$ denote the high-resolution discrete object defined on a computational grid, and let $I^{(b)} \in \mathbb{R}^{M \times M}$ denote the pixel-binned measurement. The

forward model can therefore be expressed in discrete form as follows:

$$I^{(b)} = \mathcal{B}_b (|\mathcal{P}_z(O \odot S)|^2). \quad (9)$$

Solvability of the inverse problem depends on the ratio between the number of measurements and the number of unknown object pixels within the support. Defining the measurement-to-unknown ratio as

$$\eta = \frac{N_{\text{meas}}}{N_{\text{unknown}}}, \quad (10)$$

where N_{unknown} denotes the number of pixels inside the support Ω and N_{meas} denotes the number of independent detector samples. By recording the diffraction pattern on a sensor area larger than the object support, the captured diffraction field extends beyond the physical bounds of the object. This increases measurement redundancy and the ratio η , which inherently improves the stability of the reconstruction.

3. INVERSE PROBLEM AND RECONSTRUCTION ALGORITHM

Our goal is to recover a high-resolution complex object field $O \in \mathbb{C}^{M \times N}$ from undersampled diffraction intensity measurements $I_z^{(b)}$ [Eq. (8)] by minimizing a regularized loss function $\mathcal{L}$ that balances data fidelity with prior knowledge of object sparsity. This is posed as the following variational inverse problem:

$$\begin{aligned} O^* &= \arg \min_{O \in \mathbb{C}^{M \times N}} \mathcal{L}(O) \\ &= \arg \min_{O \in \mathbb{C}^{M \times N}} \left\{ \frac{1}{2} \left\| \sqrt{I_z^{(b)}} - \sqrt{\mathcal{B}_b(|\mathcal{P}_z(O \odot S)|^2)} \right\|_2^2 + \alpha \text{TV}(O) \right\}. \end{aligned} \quad (11)$$

The first term enforces data fidelity through an ℓ_2 loss between measured and predicted square-root intensities, while the second term is an isotropic TV regularizer that promotes piecewise-smoothness while preserving edges. Here, the regularization parameter $\alpha > 0$ controls the trade-off between noise suppression and feature preservation.

A. Accelerated Reconstruction Using FISTA

The optimization problem in Eq. (11) is solved using a monotonic variant of the fast iterative shrinkage-thresholding algorithm (FISTA) [41,42], which is well suited for composite objectives consisting of a smooth data-fidelity term and a non-smooth TV regularizer [40]. Compared to standard gradient descent (GD) [45], which typically converges at $\mathcal{O}(1/k)$ in ill-conditioned problems, FISTA incorporates Nesterov acceleration to achieve faster convergence (see Supplement 1, Section A, Figs. S1 and S2). At iteration k , an auxiliary estimate y_k is computed as a weighted sum of the current iterate O_k and the previous update direction ($O_k - O_{k-1}$), weighted by the momentum coefficient β_k [see Eq. (14)]. The coefficient β_k is dynamically updated using a scalar acceleration parameter sequence t_k (initialized as $t_1 = 1$). This acts as a look-ahead step

before applying the gradient update. The update equations are given by

$$t_{k+1} = \frac{1 + \sqrt{1 + 4t_k^2}}{2}, \quad (12)$$

$$\beta_k = \frac{t_k - 1}{t_{k+1}}, \quad (13)$$

$$y_k = O_k + \beta_k(O_k - O_{k-1}), \quad (14)$$

$$O_{k+1} = y_k - \eta \nabla \mathcal{L}(y_k), \quad (15)$$

where η is the step size and $\nabla \mathcal{L}(y_k)$ denotes the gradient of the objective function evaluated at the auxiliary point. Evaluating the gradient at y_k enables the algorithm to achieve accelerated convergence. To improve robustness, a monotonic restart strategy is employed. If the objective increases after an update, i.e., $\mathcal{L}(O_{k+1}) > \mathcal{L}(O_k)$, the momentum is reset by setting $t_{k+1} = 1$, effectively reverting to a standard gradient step and suppressing oscillatory divergence.

B. Reconstruction Procedure

The reconstruction is initialized by upsampling the measured intensity $I_z^{(b)}$ to the high-resolution computational grid as I_z^{HR} and back-propagating its square-root intensity (amplitude) to the object plane

$$O^{(0)} = \mathcal{P}_z \left(\sqrt{I_z^{\text{HR}}} \right).$$

The object field is then iteratively updated using a monotonic FISTA scheme. At iteration k , an extrapolated estimate is formed as

$$y^{(k)} = O^{(k)} + \beta_k(O^{(k)} - O^{(k-1)}),$$

where β_k is the Nesterov acceleration parameter. The predicted measurement is computed via the pixel-aware forward model,

$$I_{\text{pred}}^{(k)} = \mathcal{B}_b \left(|\mathcal{P}_z(y^{(k)} \odot S)|^2 \right).$$

The object estimate is updated by

$$O^{(k+1)} = y^{(k)} - \eta \nabla \mathcal{L}(y^{(k)}),$$

followed by support projection $O^{(k+1)} \leftarrow O^{(k+1)} \odot S$. A monotonic restart is applied whenever the objective increases. Iterations proceed until convergence of the relative update $\|O^{(k+1)} - O^{(k)}\|_2 / \|O^{(k)}\|_2$. The entire reconstruction framework, including the pixel-aware forward model, was implemented as differentiable layers in Python using TensorFlow. Further implementation details and convergence traces are provided in Sections A and B of Supplement 1.

4. SIMULATION SETUP AND EVALUATION METRICS

For numerical experiments, we have used two distinct binary test images and two natural images as phase only objects. All the

objects are defined on a high-resolution (HR) computational grid with a sampling pitch of $\delta x = 0.25 \mu\text{m}$ and illumination wavelength $\lambda = 500 \text{ nm}$, normalized to phase range of $[0, \pi/2]$. This phase range was selected to model weak-to-moderate phase objects commonly imaged using DLIHM while avoiding severe phase wrapping, thereby enabling evaluation of subpixel phase recovery independently of phase-unwrapping errors. The sampling pitch ($0.25 \mu\text{m}$) is used only as a computational sampling grid to satisfy Nyquist sampling of features of spatial frequencies ($1/\lambda$) in propagated field. For these simulations, the object amplitude was assumed spatially uniform with $A(x, y) = 1$ inside the object support region, i.e., non-absorbing pure-phase objects and zero outside (non-transmitting). For initial proof of concept studies and parametric sweeps, including analysis of noise and quantization effects, we used a 192×256 pixels "IITD-SeNSE" image. This small grid was used to reduce computational complexity and time. For the formal quantification of resolution and PSR performance of our method under realistic physical conditions, we used a 1152×1024 cropped portion of the USAF 1951 resolution chart (Groups 6–11) [46]. To further validate the performance of the proposed method, we used the "cameraman" and "gravel" images (size 512×512) from the scikit-image dataset [47]. To implement the support constraint and simulate the recording of diffraction intensity measurements on a detector with a larger area relative to the object support, these images were embedded within a larger zero-padded field. This padding defines the region outside object support area, in which the field is enforced to zero during reconstruction. The extent of this padding defines the oversampling ratio (σ) as the linear ratio between the total computational domain and the object support. By increasing σ from 4 to 8, the number of independent intensity measurements relative to the unknown object pixels were increased, which improves the conditioning of the inverse problem and enables stable image reconstruction with subpixel resolution. Diffraction intensity measurements were generated by propagating the support-constrained HR object field over propagation distances of $z = 0.35\text{--}6 \text{ mm}$ using the angular spectrum propagation method. To model the finite pixel integration of a discrete CMOS/CCD detector, spatial binning ($b \times b$) was applied to the HR diffraction field to generate low-resolution measurements $I_z^{(b)}$. The effective detector pixel pitch of the low-resolution grid becomes $b \times 0.25 \mu\text{m}$. Specifically, binning factors $b = 4, 8$, and 16 correspond to effective detector pixel pitches of $1, 2$, and $4 \mu\text{m}$, respectively, which are within the range of pixel sizes of image sensors commonly used for DLIHM. The simulated binned diffraction intensity measurements were further corrupted with Poisson shot noise corresponding to mean photon counts of N_p photons/pixel. Regularization weight parameter $\alpha = 0.15$ was used for binary images and $0.02\text{--}0.04$ for the non-binary complex natural images. Reconstruction fidelity was quantified using the phase signal-to-noise ratio (SNR) and the Pearson correlation coefficient (PCC), and structural similarity index metric (SSIM) of the reconstructed field after unwrapping [48], and was calculated against the high-resolution ground-truth. Mathematical definitions of the evaluation metrics, corresponding quantitative values, and details of the photon count normalization and Poisson noise model are provided in Supplement 1.

5. RESULTS AND DISCUSSION

A. Performance Comparison and Forward Model Validation

Performance of the proposed SCAR-PSR framework was evaluated using simulated hologram at $8 \times$ spatial binning, corresponding to an effective detector pixel size of $2.0 \mu\text{m}$, while reconstruction was carried out on a $0.25 \mu\text{m}$ computational grid. Figure 4 compares three reconstruction strategies: (i) direct single-shot back-propagation of the binned hologram, (ii) iterative reconstruction using naively upsampled measurements (NU-PSR) that assumes point sampling [6], and (iii) the proposed SCAR-PSR framework, which explicitly incorporates the pixel binning operator within the forward model while enforcing finite object support. To ensure a rigorous and fair comparison, our implementation of NU-PSR uses the exact same FISTA-based optimization scheme and support constraints as SCAR-PSR; however, it intentionally omits the spatial binning operator ($\mathcal{B}_b$) from the forward model and uses an upsampled hologram as input to simulate the classical assumption of point-sampled measurements [6]. Direct back-propagation provides completely degraded reconstruction due to severe attenuation of high spatial frequencies and no constraints are implemented during reconstruction. NU-PSR provides improved reconstruction with fine fringe preservation and also improves overall contrast, but it has reconstruction artifacts that degrades reconstruction quality as it neglects the physical averaging inherent to finite detector pixels. In contrast, SCAR-PSR achieves high-fidelity phase reconstruction closely matching the ground-truth, attaining SNR, PCC, and SSIM of approximately 24.1 dB, 0.9981, and 0.9128, respectively, in comparison to 12.57, 0.9719, and 0.5285 in the case of NU-PSR. These results demonstrate that support constraints alone are insufficient for super-resolution unless accompanied by accurate modeling of pixel integration, establishing pixel-aware forward modeling as a necessary condition for stable single-shot

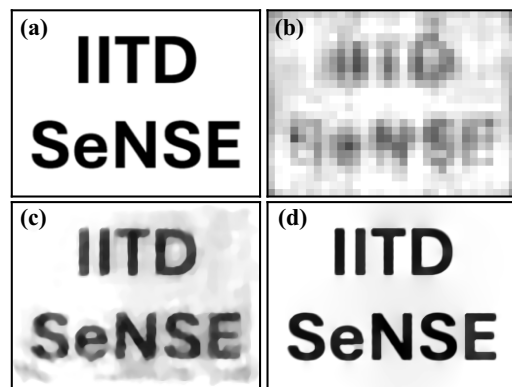


Fig. 4. Phase reconstruction comparison under physical pixel binning (initial object and reconstruction pixel sizes of $0.25 \mu\text{m}$, $8 \times$ binning, and effective recording pixel size $= 2 \mu\text{m}$): (a) ground-truth high-resolution phase object. (b) Single-shot reconstruction obtained by direct back-propagation of the binned low-resolution hologram. (c) Iterative reconstruction using an upsampled low-resolution hologram without modeling the detector binning process (naive upsampling approach). (d) Reconstruction using the proposed SCAR-PSR method, which explicitly incorporates the pixel binning model within the forward propagation framework.

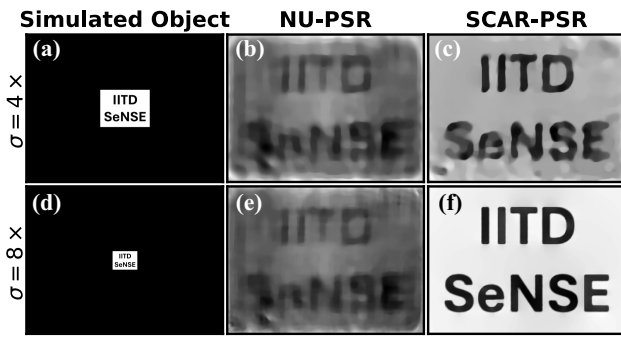


Fig. 5. Phase reconstruction from highly undersampled measurements at binning factor $b = 16$ (effective detector pixel size $4 \mu\text{m}$) and propagation distance $z = 0.5 \text{ mm}$ for oversampling factors $\sigma = 4\times$ (top row) and $\sigma = 8\times$ (bottom row). The first column shows the simulated high-resolution object with increased zero-padding to enlarge the effective recording aperture. Reconstruction using NU-PSR shows degraded reconstruction and loss of high spatial frequency information in the second column. The third column, SCAR-PSR, shows reconstruction of fine features consistently outperforms the NU-PSR, particularly at $\sigma = 8\times$.

phase super-resolution in DLIHM under realistic sampling conditions.

B. Role of Compact Object Support and Oversampling

To investigate the requirement of compact object support and relatively larger measurements to achieve PSR, we performed reconstruction using the measurement $I_z^{(b)}$ with different

oversampling ratios $\sigma = 4\times$ and $8\times$. For a severe $16\times$ binning case ($4.0 \mu\text{m}$ pixel pitch), an oversampling ratio of $\sigma = 4$ is insufficient to uniquely constrain the inverse problem, leading to degraded reconstruction. Although SCAR-PSR provides improved reconstruction than the NU-SR as shown in Figs. 5(b) and 5(c), respectively, but smaller features are lost. However, by extending the computational measurement domain $\sigma = 8\times$ and using SCAR-PSR, the increased measurement redundancy and correct forward model stabilizes the reconstruction and provides PSR and no loss of small features even under severe undersampling ($16\times$).

C. Reconstruction of Natural Non-Binary Images

To further evaluate the performance of the proposed SCAR-PSR method on natural images with complex texture phase profiles, it was applied to two standard 512×512 grayscale images: “cameraman” and “gravel” [47]. Binned diffraction intensity measurements were simulated at a propagation distance $z = 0.6 \text{ mm}$ using a spatial binning factor $b = 4$ (effective pixel size $1 \mu\text{m}$) and an oversampling ratio $\sigma = 8$. A TV regularization weight of $\alpha = 0.02$ was used for the reconstruction. Figure 6 shows the recovery of features finer than the native camera resolution ($1 \mu\text{m}$) from undersampled, low-resolution diffraction intensity measurements. Because natural, continuous-tone objects contain significantly higher information entropy than binary step-phase objects, their recovery is mathematically more challenging and requires careful tuning of the regularization parameters to balance structural preservation with artifact suppression. Further performance evaluation in the presence of shot noise is presented in Supplement 1 (Fig.

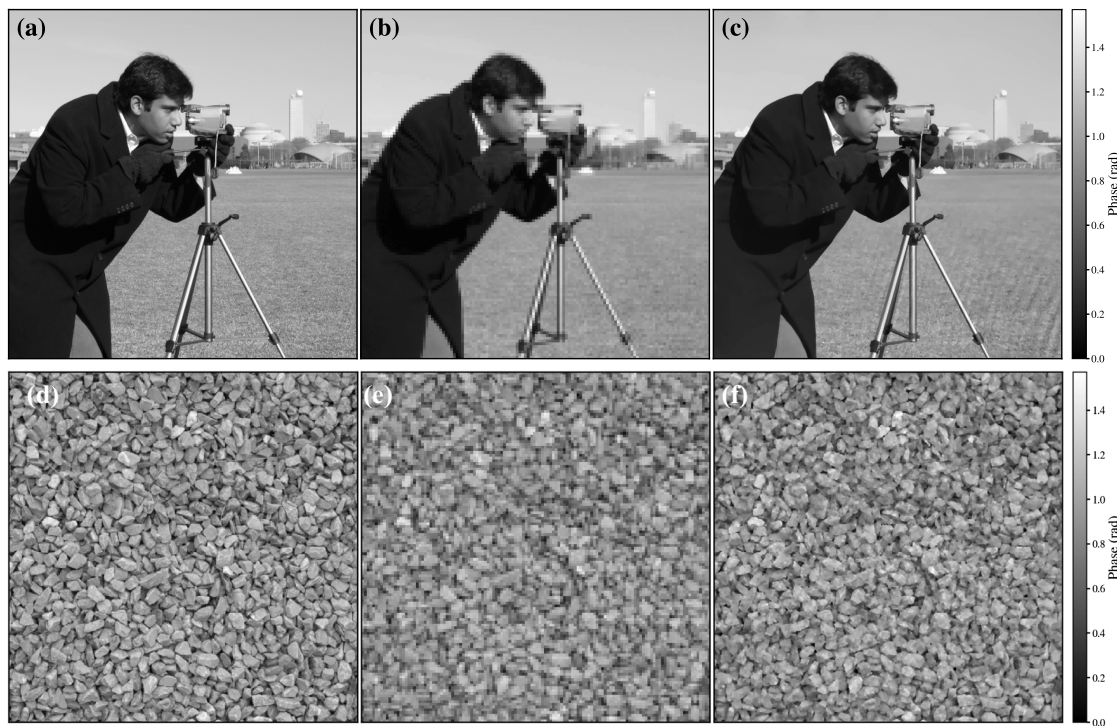


Fig. 6. Reconstruction of non-binary images from undersampled diffraction intensity measurements using SCAR-PSR. (a) and (d) show ground-truth phase objects, (b) and (e) show the undersampled image at camera (recording) resolution by binning, considering a pixel size of $1 \mu\text{m}$ ($b = 4$), and (c) and (f) show reconstructed phase from undersampled diffraction intensity measurements ($b = 4$ and effective pixel size of $1 \mu\text{m}$).

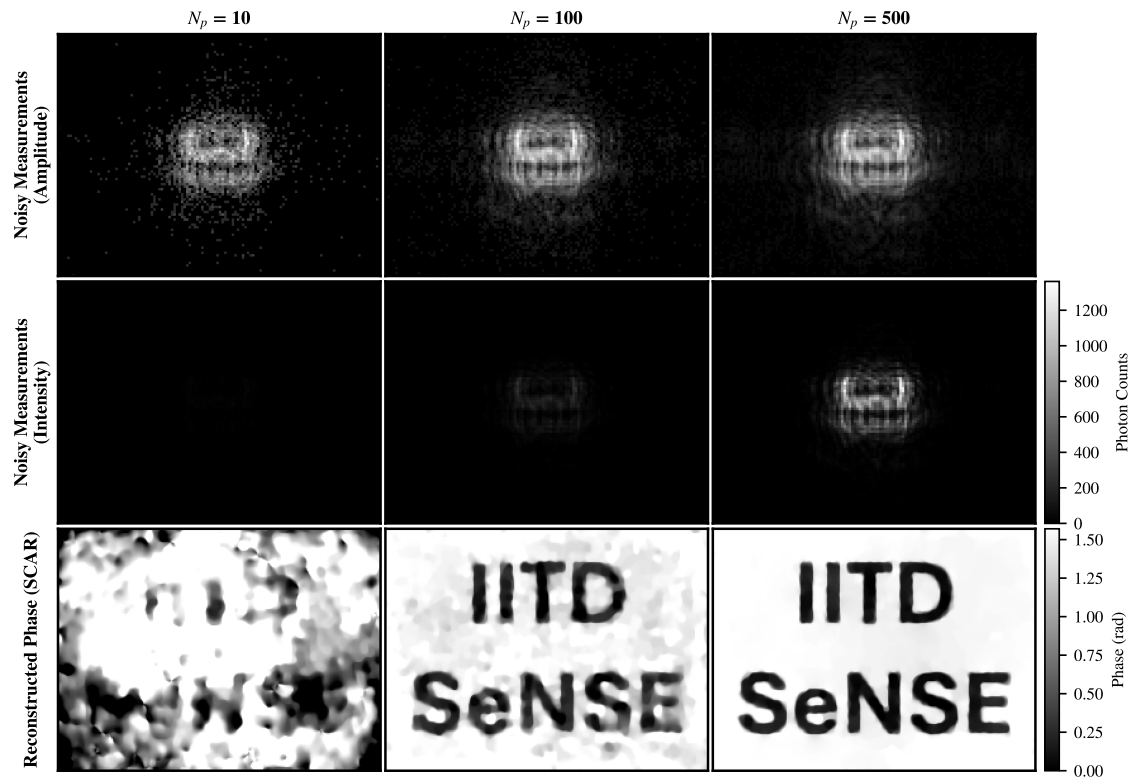


Fig. 7. Effect of Poisson noise on SCAR-PSR phase reconstruction. Columns denote simulations with average photon counts (N_p) of 10, 100, and 500 per pixel. Top row: noisy diffraction amplitude ($\sqrt{I_z}$), displayed to visually compress the high dynamic range and better reveal the low-contrast diffraction fringes. Middle row: corresponding noisy diffraction intensity (I_z). Bottom row: phase recovered using the proposed SCAR-PSR method.

S10) validating the subpixel phase recovery of complex texture objects from undersampled diffraction intensity measurements in presence of noise.

D. Algorithmic Stability, Convergence, and Robustness to Detector Limitations

Algorithmic stability was assessed through convergence behavior and sensitivity to propagation distance (Supplement 1, Figs. S1–S5). Figures S4–S5 of Supplement 1 compares FISTA and GD reconstructions across propagation distances ranging from $z = 0.15$ to 0.75 mm. The FISTA-based optimization consistently achieves higher phase fidelity and reduced reconstruction artifacts over the examined z -distance range with a relatively smaller number of iterations (Supplement 1, Figs. S2 and S3). Quantitatively for FISTA-based reconstruction, the phase SNR, PCC, and SSIM peak near $z \approx 0.35$ – 0.5 mm, indicating optimal conditioning of the inverse problem within this Fresnel regime. In contrast, GD exhibits slower convergence and reduced robustness, particularly as propagation distance deviates from the optimal region. At larger propagation distances ($z \geq 0.75$ mm), both methods show degradation in phase SNR, PCC, and SSIM, consistent with increased model sensitivity and reduced conditioning of the forward operator due to decreased effective NA. Robustness to practical detector limitations was further evaluated under quantization (Supplement 1, Figs. S7–S9) and Poisson shot noise (Figs. 7 and 8). The reconstructed phase SNR saturates at approximately 24 dB beyond

six-bit detector precision, indicating that reconstruction performance in the proposed framework is not strongly limited by typical CMOS quantization levels, consistent with prior studies showing that moderate detector bit-depths are often sufficient for acceptable digital holographic reconstruction quality [49,50], but rather by information loss introduced by spatial binning and photon statistics. The photon level was controlled using the average photon count (N_p) per detector pixel within the primary diffraction region. Additional implementation details of the shot noise model and normalization procedure are provided in Supplement 1 (Section C).

Under Poisson shot noise, stable reconstruction is maintained down to approximately 500 average photons per detector pixel in the primary diffraction region. At lower photon levels (100 photons/pixel), degradation in the reconstructed image becomes noticeable due to the increased shot-noise fluctuations expected at low photon counts, as shown in Fig. 7. The present analysis isolates photon shot noise and quantization as fundamental acquisition constraints. In practical CMOS/CCD sensors, additional electronics-related noise sources such as read noise, dark current, fixed-pattern noise, and photoresponse non-uniformity (PRNU) may also influence reconstruction quality depending on signal level and sensor calibration [51].

E. Resolution Assessment Using USAF Target

Numerical resolution performance was further evaluated using a simulated USAF–1951 resolution test target reconstructed

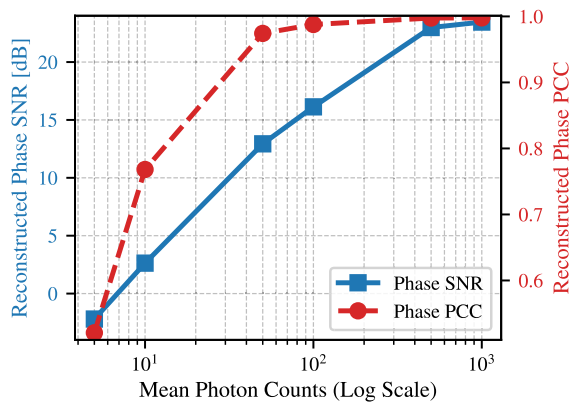


Fig. 8. Performance of SCAR-PSR for phase reconstruction under shot noise for different level of photon counts. Blue and red curves show SNR and PCC of reconstructed image with respect to the high-resolution ground-truth image.

from undersampled diffraction intensity measurements at $z = 0.6$ mm with $8\times$ binning (effective detector pixel size of $2\text{ }\mu\text{m}$). Figure 9 shows comparison of the ground-truth high-resolution (GT-HR) phase and corresponding low-resolution (GT-LR) phase, showing original object image at camera resolution, features finer than the Group 8 Element 1 are not resolvable, demonstrating pixel limited resolution (half period) of $2\text{ }\mu\text{m}$, and the proposed SCAR-PSR reconstruction. The SCAR-PSR reconstruction clearly resolves up to Element 3 of Group 10, corresponding to a minimum resolvable line width of approximately $0.4\text{ }\mu\text{m}$, demonstrating an effective resolution enhancement of approximately $5\times$ relative to the native detector sampling pitch. Line profiles extracted across the resolved bar patterns exhibit clear separation between adjacent features and preservation of fringe contrast, confirming recovery of spatial frequency components beyond the nominal detector cutoff. These results demonstrate that pixel-aware forward modeling

combined with support-constrained inversion enables stable recovery from aliased diffraction measurements and facilitates deterministic single-shot PSR in DLIHM.

6. CONCLUSION

In this paper, a support-constrained, pixel-aware, single-shot phase super-resolution framework for DLIHM has been presented. By explicitly incorporating the deterministic physics of finite detector pixel integration into the forward imaging model and simultaneously enforcing a strict finite spatial support constraint, the proposed SCAR-PSR methodology successfully recovers the high-resolution complex optical field from a single, severely undersampled diffraction intensity measurement. Central to the success of this approach is the strategic utilization of the object-domain oversampling ratio. Provided the physical spatial extent of the specimen is sufficiently compact relative to the expanded discrete computational domain, the resulting topological redundancy rigorously stabilizes the highly ill-posed inverse problem, facilitating the deterministic analytic continuation of spatial frequencies far beyond the sensor's fundamental Nyquist–Shannon limit.

Numerical studies demonstrate the robustness of this framework even under extreme undersampling conditions. Using an $8\times$ computational window, we were able to achieve resolution gains of approximately $5\times$ relative to native detector sampling and achieved a half-period resolution of $0.4\text{ }\mu\text{m}$, close to the coherent diffraction limit ($\lambda/2 = 0.25\text{ }\mu\text{m}$). Robustness to photon noise, quantization, and variations in propagation distance was also observed. The resolution can possibly be further increased by utilizing the larger computational window, provided sufficient oversampling is used.

Crucially, the upper bound of this resolution enhancement is fundamentally governed by the object-domain oversampling ratio. In this study, the maximum achievable oversampling ratio was strictly constrained by the finite computational window size

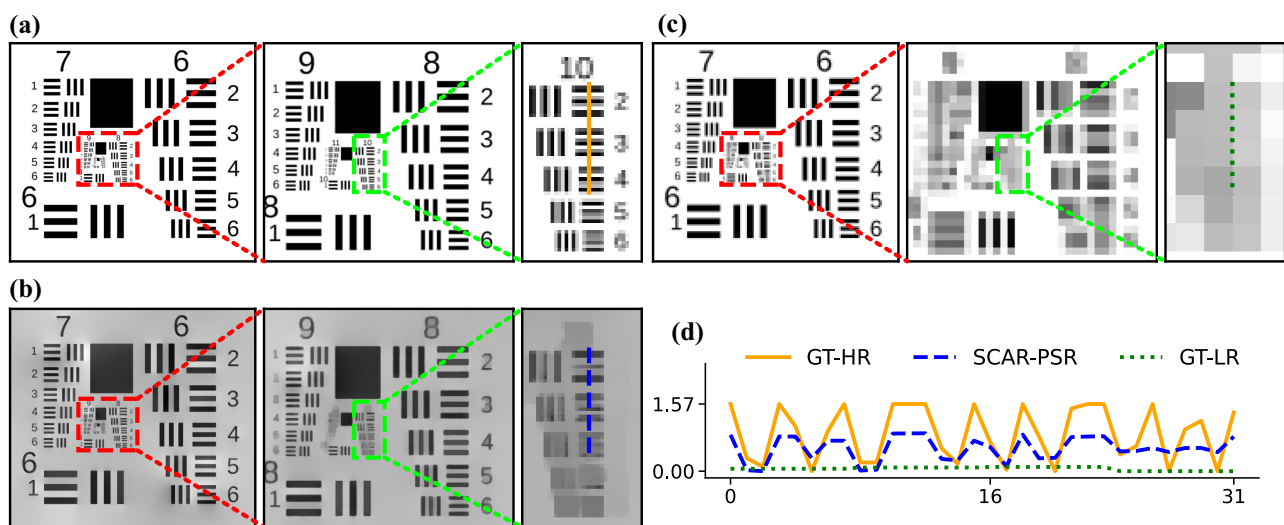


Fig. 9. Reconstruction of the USAF-1951 resolution chart using the proposed single-shot, support-constrained PSR method: (a) ground-truth high-resolution chart, (b) reconstructed phase at a binning factor of $b = 8$ and propagation distance $z = 0.6$ mm, and (c) downsampled ground-truth illustrating the pixel-limited camera resolution. Magnified insets show that the proposed SCAR-PSR method clearly resolves features down to Group 10, Element 3, whereas the downsampled image fails to resolve even Group 8, Element 2 due to severe aliasing. This demonstrates a significant super-resolution gain ($5\times$) beyond the sensor's native pixel pitch.

(8192 × 9216 pixels) with an oversampling ratio of 8×, due to the intensive memory requirements of the discrete Fourier transform operations. Higher mathematical redundancy is required for further resolution gains, allowing the single-shot architecture to more closely approach the absolute coherent diffraction limit that requires higher oversampling ratio. These results highlight the importance of jointly accounting for detector physics and object support constraints in single-shot holographic super-resolution, and establish SCAR-PSR method as an effective mechanism for improving problem conditioning without additional hardware complexity. The methodology relies on enforcing a known finite object support. Consequently, the physical spatial extent of the biological specimen or sample must be sufficiently compact relative to the active area of image sensor in order to get sufficient redundancy for solving the inverse problem.

Future work will focus on validating the performance of the proposed method across a wider class of samples, experimental verification, and extension to dynamic biological imaging scenarios, as well as investigating alternative optimization frameworks such as the alternating direction method of multipliers (ADMMs), conjugate-gradient-based optimization, quasi-Newton methods, proximal splitting algorithms, and deep unrolled optimization frameworks with learned priors for improving convergence speed, reconstruction stability, and computational efficiency.

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Data availability. Data underlying the results presented in this paper are not publicly available at this time but may be obtained from the authors upon reasonable request.

Supplemental document. See Supplement 1 for supporting content.

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