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Physics-informed neural fields enable blind aberration correction for partially coherent quantitative phase imaging

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Abstract: Partially coherent quantitative phase imaging (QPI) underpins label-free microscopy and optical metrology, providing stable, speckle-suppressed phase measurement with a brightfield-compatible platform and resolution beyond the coherent diffraction limit. However, its image formation is governed by a high-dimensional bilinear forward model, making linearized analytic inversions such as differential phase contrast (DPC) prone to model mismatch and biased reconstruction under large phase excursions, strong absorption, and optical aberrations. Here, we introduce USDPC, a universal neural-field solver for DPC, that performs physics-constrained, unsupervised inversion of the strict nonlinear intensity-to-phase relationship under partially coherent illumination. USDPC represents the specimen's complex transmittance and pupil aberrations as implicit neural fields and jointly optimizes them via a differentiable bilinear forward operator, enabling accurate phase recovery beyond the weak-object regime while self-calibrating unknown aberrations without additional calibration data or acquisition overhead. Comprehensive simulations and experimental validations on microlens arrays, resolution targets, stained histological sections, and live HeLa cells demonstrate the effectiveness and universality of USDPC, and highlight physics-informed neural fields as a versatile computational framework for solving challenging nonlinear inverse problems in computational imaging and beyond.

Keywords: phase retrieval; nonlinear inverse problem; aberration correction; neural fields; differential phase contrast microscopy

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1 Introduction

When illuminated by an electromagnetic field, spatial variations in dielectric properties between an object and its surrounding medium perturb the scattered field¹. Inverse scattering seeks to reconstruct the object's structural features from these scattered signals using physical models of object-field interactions^{2,3}. This technique plays a pivotal role in fundamental wave physics and underpins diverse applica-

tions, including biomedical imaging, geophysical exploration, and non-destructive evaluation^{4–6}. However, inverse scattering is inherently more challenging than the forward counterpart because of its nonlinearity, ill-posedness, and high computational cost. Conventional approaches often linearize the forward model by introducing approximations or simplifying assumptions, reformulating the inverse problem into a linear convex optimization task^{4,7–10}. Regularization strategies are subsequently employed to alleviate

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ill-posedness, stabilizing the solution and suppressing artifacts amplification^{11–13}. While such linearization facilitates efficient computation and improves stability, it inevitably compromises reconstruction accuracy, as it fails to capture the nonlinear interactions intrinsic to complex scattering processes. Nonlinear models more faithfully represent the underlying physics and improve consistency with experimental data, though at the cost of greater algorithmic complexity and data redundancy^{14–16}.

Quantitative phase retrieval constitutes a central class of nonlinear inverse scattering problems that aims to recover the phase of an optical wavefront from intensity-only measurements¹⁷. This methodology has promoted the development of quantitative phase imaging (QPI), forming the foundation of modern label-free microscopy and advanced optical metrology. In coherent imaging, iterative phase retrieval methods, exemplified by the Gerchberg-Saxton algorithm, provide pioneering inverse-problem solutions^{18,19}. However, such approaches suffer from ill-posedness in terms of solution existence and uniqueness, as well as slow convergence and frequent stagnation. Deterministic QPI methods based on the transport of intensity equation offer guaranteed existence and uniqueness of the solution, but the achieved spatial resolution remains fundamentally constrained by the coherent diffraction limit^{20–23}. Fourier ptychographic microscopy overcomes this limitation by performing multiple intensity acquisitions under varying illumination angles, thereby enabling simultaneous phase retrieval and super-resolution imaging^{24–26}. Nevertheless, its reliance on sequential multi-angle data acquisition leads to long acquisition times and substantial data redundancy.

Compared with coherent imaging, QPI under partially coherent illumination offers notable advantages, including speckle-suppressed phase measurement with a brightfield-compatible platform and resolution beyond the coherent diffraction limit^{27–31}. The forward image-formation process is governed by the transmission cross-coefficient (TCC) model, which is formulated as a four-dimensional representation in the spatial-frequency domain^{32,33}. However, the inherently nonlinear (bilinear) nature of the model, together with its high dimensionality, imposes a substantial computational burden, rendering direct inversion generally impractical. Therefore, partially coherent QPI techniques, such as differential phase contrast (DPC) microscopy, typically rely on simplifying assumptions, including the weak object approximation and the ideal-pupil assumption, to linearize the inherently nonlinear forward model for analytical inversion^{31,34,35}. However, these assumptions often break down in practical scenarios involving strong absorption, large phase variations, or unknown optical aberrations, thereby limiting the reconstruction accuracy and quantitative fidelity^{36,37}. To alleviate these limitations, nonlinear iterative reconstruction methods have been developed to extend QPI beyond the weak object approximation, enabling more accurate phase

recovery for large-phase samples³⁶. Aberration-correction techniques have also been proposed to compensate for unknown optical aberrations by refining the transfer function or jointly estimating the pupil function within the conventional linear framework^{38–40}. Despite these advances, existing approaches address nonlinear inversion and aberration correction separately, and a unified framework capable of simultaneously overcoming the weak object approximation and unknown aberrations remains lacking. Consequently, QPI functions primarily as imaging modalities and fails to provide the precision necessary for rigorous optical metrology.

Recent advances in deep learning have provided new avenues for addressing these limitations by leveraging data-driven nonlinear mappings to approximate the complex intensity-to-phase relationship^{41–45}. Such approaches have demonstrated the potential to overcome convergence instabilities and improve reconstruction accuracy in nonlinear inverse problems^{46–48}. However, conventional end-to-end neural network models fundamentally operate as black-box mappings between measurement and object domains, lacking explicit physical interpretability^{49,50}. Their performance is heavily dependent on the availability of large-scale, high-quality labeled datasets, which remain scarce in practical phase retrieval scenarios due to the difficulty of acquiring ground-truth phase information under complex scattering conditions. Moreover, purely data-driven methods often suffer from limited robustness and poor generalization when applied across varying imaging domains or system configurations. Along this direction, untrained neural-network-based methods, exemplified by Deep Phase Decoder, have demonstrated that inverse scattering problems in coherent imaging can be solved through physics-driven, unsupervised optimization without requiring labeled datasets or supervised training^{51,52}.

Inspired by these developments, we propose a universal neural-field solver for differential phase contrast microscopy (USDPC), which performs physics-constrained, unsupervised inversion of the strict nonlinear intensity-to-phase relationship under partially coherent illumination. USDPC represents the specimen's complex transmittance and pupil aberrations as implicit neural fields and jointly optimizes them via a differentiable bilinear forward operator, enabling accurate phase recovery beyond the weak-object regime while self-calibrating unknown aberrations without additional calibration data or acquisition overhead. Notably, USDPC operates under the standard DPC data acquisition scheme, ensuring compatibility with existing experimental setups. Through comprehensive simulations and experiments on standard microlens arrays, resolution targets, and biological specimens, we demonstrate that USDPC outperforms conventional DPC in phase accuracy, robustness to large excursions, and resilience to optical aberrations. These results not only establish USDPC as a practical approach for

high-precision QPI but also highlight the physics-informed neural fields as a versatile computational framework for solving challenging nonlinear inverse problems in computational imaging and beyond.

2 Principle

2.1 Partially coherent imaging forward model

Partially coherent imaging can be described as a nonlinear (bilinear) process^{32,33}, where the recorded image at the image plane is determined by the interaction between the object complex transmission function $t(\mathbf{r})$ and the illumination distribution $S(\mathbf{u})$ at the aperture diaphragm plane:

$$I(\mathbf{r}) = \iint S(\mathbf{u}) \hat{T}(\mathbf{u}_1) \hat{T}^*(\mathbf{u}_2) P(\mathbf{u} + \mathbf{u}_1) P^*(\mathbf{u} + \mathbf{u}_2) e^{j2\pi\mathbf{r}(\mathbf{u}_1 - \mathbf{u}_2)} d\mathbf{u}_1 d\mathbf{u}_2 d\mathbf{u} \quad (1)$$

where $\mathbf{u} = (u_x, u_y)$ represents the spatial frequency coordinates corresponding to spatial coordinates $\mathbf{r} = (x, y)$. The amplitude of the pupil function corresponds to an ideal low-pass filter, while its phase component quantitatively characterizes the system's wavefront aberrations. $\hat{T}(\mathbf{u})$ is the Fourier transforms of object complex transmittance function $t(\mathbf{r}) = e^{-a(\mathbf{r}) + j\phi(\mathbf{r})}$, where $a(\mathbf{r})$ and $\phi(\mathbf{r})$ correspond to the absorption and phase components, respectively. By isolating object-dependent parameters, the system-dependent component is formally defined as the transmission cross coefficient, which is also termed transfer function for partially coherent image formation:

$$\text{TCC}(\mathbf{u}_1, \mathbf{u}_2) = \iint S(\mathbf{u}) P(\mathbf{u} + \mathbf{u}_1) P^*(\mathbf{u} + \mathbf{u}_2) d\mathbf{u} \quad (2)$$

It quantitatively characterizes the imaging system's modulation operator acting on the object's cross-spectrum density $\hat{T}(\mathbf{u}_1) \hat{T}^*(\mathbf{u}_2)$, serving as a fundamental basis for analyzing partially coherent imaging systems. Equation (1) can be expressed accordingly as

$$I(\mathbf{r}) = \iint \hat{T}(\mathbf{u}_1) \hat{T}^*(\mathbf{u}_2) \text{TCC}(\mathbf{u}_1, \mathbf{u}_2) e^{j2\pi\mathbf{r}(\mathbf{u}_1 - \mathbf{u}_2)} d\mathbf{u}_1 d\mathbf{u}_2 \quad (3)$$

The relationship between the measured intensity and the object complex transmittance spectrum is inherently nonlinear (or bilinear), as the intensity spectrum arises from the coupling of spatial frequency pairs within the object complex amplitude spectrum. This nonlinear interaction precludes the direct derivation of an analytical expression for the object function, significantly complicating both image reconstruction and phase retrieval.

2.2 Linear solution to conventional DPC

As a QPI method with partially coherent illumination, DPC typically requires the acquisition of four intensity images $\{I_i(\mathbf{r}), i = 1, 2, 3, 4\}$ under orthogonal directional illuminations $\{S_i(\mathbf{u}), i = 1, 2, 3, 4\}$ ($S_1(\mathbf{u})$ and $S_2(\mathbf{u})$ exhibit asymmetry along one axis, while $S_3(\mathbf{u})$ and $S_4(\mathbf{u})$ exhibit asymmetry along a mutually orthogonal axis), as illustrated in Fig. 1(a). To simplify the computational process of the phase retrieval, we introduce the weak object approximation in Eq. (3), which linearizes the complex transmittance function as^{53–55}:

$$t(\mathbf{r}) \approx 1 - a(\mathbf{r}) + j\phi(\mathbf{r}) \quad (4)$$

By performing the Fourier transform and substituting it into Eq. (3), while neglecting higher-order scattering terms, the simplified linearized expression in the Fourier domain for the measured intensity can be derived as^{53,55}

$$I(\mathbf{u}) = B\delta(\mathbf{u}) + A(\mathbf{u})H_a(\mathbf{u}) + j\Phi(\mathbf{u})H_p(\mathbf{u}) \quad (5)$$

where B is the direct current (DC) term that represents the background intensity. $A(\mathbf{u})$ and $\Phi(\mathbf{u})$ correspond to the Fourier transforms of $a(\mathbf{r})$ and $\phi(\mathbf{r})$. $H_a(\mathbf{u})$ and $H_p(\mathbf{u})$ represent the absorption transfer function (ATF) and phase transfer function (PTF), respectively, characterizing the quantitative relationship between measured intensity and object's amplitude and phase.

Owing to the even-symmetric nature of ATF and the odd-symmetric nature of PTF, object's absorption and phase information can be decoupled via Eq. (5). To extract phase information of interest, differential computations are performed to suppress DC components and amplitude-induced variations, yielding intensity difference terms that contain only phase information^{35,56}, i.e., $I_1^{\text{DPC}} = (I_1 - I_2) / (I_1 + I_2)$ and $I_2^{\text{DPC}} = (I_3 - I_4) / (I_3 + I_4)$. Then, the Tikhonov regularization is used to implement intensity-to-phase inversion¹¹:

$$\phi(\mathbf{r}) = F^{-1} \left\{ \frac{\sum_{k=1}^2 [\text{WPTF}_k^*(\mathbf{u}) I_k^{\text{DPC}}(\mathbf{u})]}{\sum_{k=1}^2 |\text{WPTF}_k(\mathbf{u})|^2 + \alpha} \right\} \quad (6)$$

where k is the index of asymmetric axis, and α is the regularization factor balancing data fidelity and solution smoothness. $\text{WPTF}_k(\mathbf{u})$ represents the weak phase transfer function (WPTF) corresponding to asymmetric axis k ^{31,35,57}. Taking $\text{WPTF}_1(\mathbf{u})$ as an example, it can be expressed as

$$\text{WPTF}_1(\mathbf{u}) = \frac{\iint [S_1(\mathbf{u}') - S_2(\mathbf{u}')] [P^*(\mathbf{u}')P(\mathbf{u}' + \mathbf{u}) - P(\mathbf{u}')P^*(\mathbf{u}' - \mathbf{u})] d\mathbf{u}'}{\iint [S_1(\mathbf{u}') + S_2(\mathbf{u}')] [P^*(\mathbf{u}')P(\mathbf{u}' + \mathbf{u}) + P(\mathbf{u}')P^*(\mathbf{u}' - \mathbf{u})] d\mathbf{u}'} \quad (7)$$

As a direct quantitative descriptor of phase-to-intensity transfer, the accuracy of the WPTF fundamentally determines the fidelity of phase reconstruction. Conventional

strategies often simplify the WPTF by assuming an ideal pupil function, thereby neglecting aberration-induced perturbations. In practice, however, unknown optical aberrations

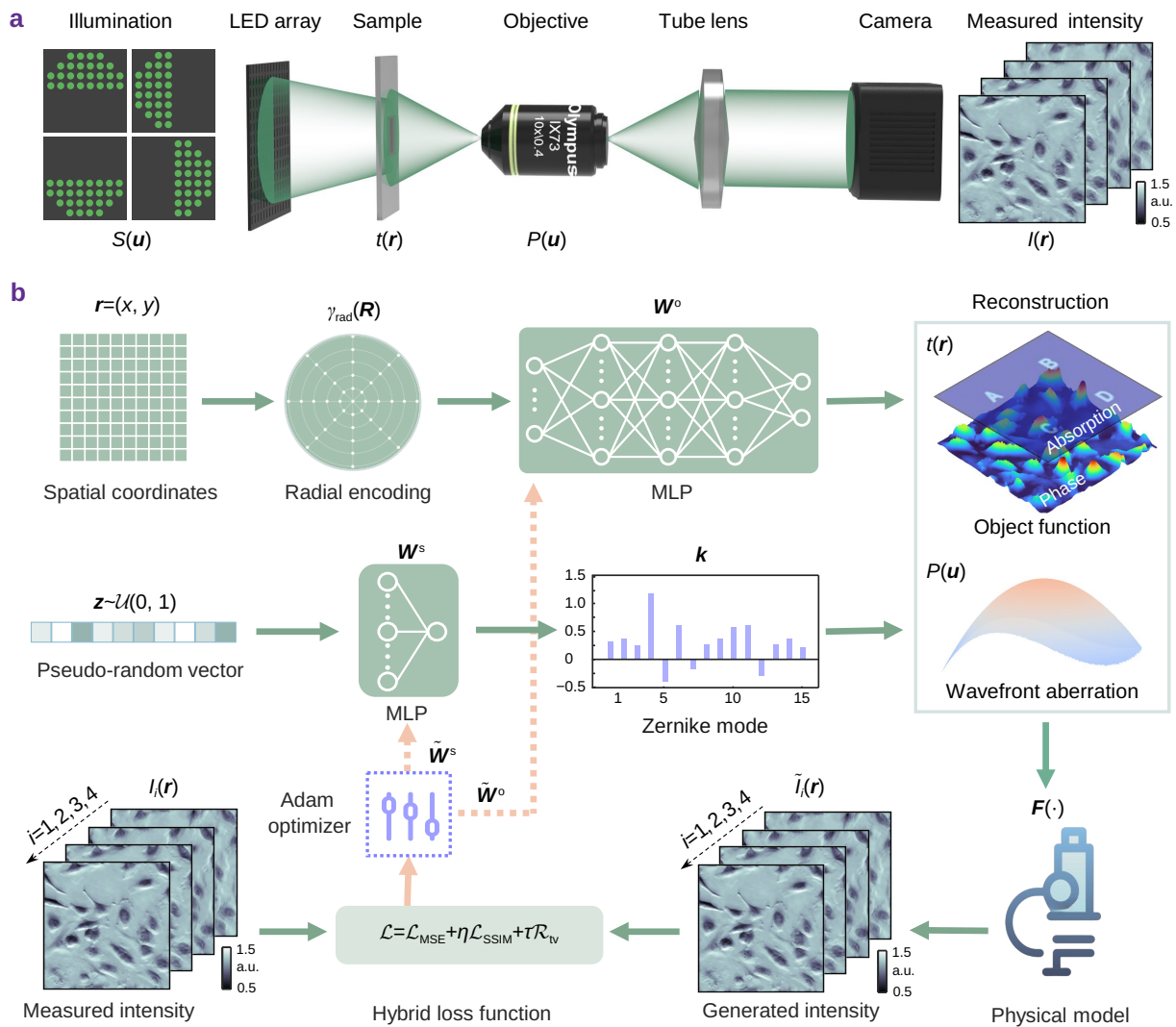


Fig. 1 | Overview of USDPC framework. (a) Schematic of the physical model for DPC imaging under partially coherent illumination. (b) Architecture and workflow of the proposed USDPC method.

inevitably couple into the reconstructed phase, producing errors and artifacts.

Overall, the phase retrieval of conventional DPC is critically constrained by two assumptions: the weak object approximation and the ideal pupil function. Under realistic conditions, these assumptions amplify nonlinear errors, limiting both the quantitative accuracy and applicability of phase retrieval, particularly for specimens with large phase excursions or complex structures. Overcoming these limitations requires a nonlinear phase retrieval framework that faithfully captures system physics and incorporates aberration compensation, thereby enabling high-precision phase reconstruction under practical imaging conditions.

2.3 Reconstruction algorithm of USDPC under neural-field framework

To achieve high-fidelity reconstruction beyond the weak-

object and ideal-pupil assumptions adopted in conventional linear DPC, we integrate the nonlinear partially coherent imaging physical model with a neural-field framework^{58–60}, as illustrated in Fig. 1(b). Specifically, USDPC represents the object complex transmittance and pupil aberrations as implicit neural fields, which are jointly optimized through a differentiable bilinear forward operator. The central architecture of USDPC comprises two MLPs. The first MLP W^o maps the spatial coordinates $r = (x, y)$ to the absorption $a(r)$ and phase $\phi(r)$ of the object, while the second MLP W^s predicts Zernike coefficients that characterize the optical aberration $P(u)$ from a one-dimensional pseudo-random vector.

For the object MLP W^o , an additional encoding module is introduced prior to network computation to overcome the limited capacity of an MLP in modeling high-frequency variations. This module transforms densely sampled Cartesian coordinates into a sparser and more discriminative

high-dimensional representation using sinusoidal rotations, thereby enhancing the network's ability to capture fine structural details and subtle spatial variations. The resulting high-dimensional encoded features can be formulated as

$$\gamma_{\text{rad}}(\mathbf{R}) = \begin{pmatrix} \sin(2^0 \pi \mathbf{E}_\theta \mathbf{R}) & \cos(2^0 \pi \mathbf{E}_\theta \mathbf{R}) \\ \vdots & \vdots \\ \sin(2^{L-1} \pi \mathbf{E}_\theta \mathbf{R}) & \cos(2^{L-1} \pi \mathbf{E}_\theta \mathbf{R}) \end{pmatrix}, \quad (8)$$

where $\mathbf{R}$ is the normalized coordinates of $\mathbf{r}$, and L represents the number of frequency scales. $\mathbf{E}_\theta$ denotes a collection of rotation matrices that rotate the coordinates by the angles θ , written as

$$\mathbf{E}_\theta = \begin{pmatrix} \sin(0\Delta\theta) & \cos(0\Delta\theta) \\ \vdots & \vdots \\ \sin(D\Delta\theta) & \cos(D\Delta\theta) \end{pmatrix}, \quad (9)$$

where $D = 2\pi/\Delta\theta$ represents the number of frequencies in the encoding space. The encoded features $\gamma_{\text{rad}}(\mathbf{R})$ are then processed by a five-layer MLP $\mathbf{W}^o$ with 256 hidden units per layer. The selection of the radial encoding and the five-layer MLP architecture was based on extensive numerical evaluation. A detailed comparison of different encoding strategies and network depths is provided in Supplementary Section 3. The output comprises two separate channels corresponding to the sample's absorption and phase, which are subsequently transformed into their respective physical parameters, thereby achieving effective decoupling. The computation performed by the MLP can be expressed as

$$\mathbf{f}_{i+1}^o = \sigma_i^o(\mathbf{g}_i^o) = \sigma_i^o(\mathbf{W}_i^o \mathbf{f}_i^o), \quad (10)$$

here $\mathbf{W}_i^o$, $\mathbf{f}_i^o$, and σ_i^o denote the weight matrix, input, and activation function of the i^{th} layer of the MLP, respectively. Specifically, $\mathbf{f}_1^o$ represents the encoded features $\gamma_{\text{rad}}(\mathbf{R})$. LeakyReLU is employed as the activation function in each hidden layer to introduce nonlinearity, while a sigmoid function is applied in the output layer to ensure bounded predictions. Finally, we perform a transformation on the MLP output to obtain the corresponding physical parameters, as described below:

$$\begin{pmatrix} \phi(\mathbf{r}) \\ a(\mathbf{r}) \end{pmatrix} = \mathbf{M} \begin{pmatrix} \mathbf{f}_{N_o+1}^{o,\phi} \\ \mathbf{f}_{N_o+1}^{o,a} \end{pmatrix}, \quad (11)$$

where $\mathbf{f}_{N_o+1}^{o,\phi}$ and $\mathbf{f}_{N_o+1}^{o,a}$ represent two output channels of the last layer of MLP $\mathbf{W}_{N_o}^o$, corresponding respectively to the phase and absorption components of the sample. $\mathbf{M}$ denotes the transformation matrix used to map these outputs to the corresponding physical parameters.

The aberration MLP $\mathbf{W}^s$ is implemented as a one-layer network that maps the one-dimensional pseudo-random vector to a set of Zernike coefficients $\mathbf{k}$. Although $\mathbf{W}^s$ is a single fully connected layer, for convenience, we also collectively refer to it as MLP, which parameterizes the aberration profile as a linear combination of Zernike polynomials:

$$\mathbf{k} = T\sigma^s(\mathbf{g}^s) = T\sigma^s(\mathbf{W}^s \mathbf{f}^s), \quad (12)$$

where σ^s is the LeakyReLU activation function, and $\mathbf{f}^s$ is taken as the input of the pseudo-random vector. T is a linear transformation matrix. Furthermore, the aberration can be expressed as

$$P(\mathbf{u}) = \text{circ}\left(\frac{\mathbf{u}}{\text{NA}/\lambda}\right) e^{j \sum_m^M \mathbf{k}(m) Z_m(\mathbf{u})}, \quad (13)$$

where $\text{circ}(\mathbf{u}/(\text{NA}/\lambda))$ represents an ideal low-pass filter with a cutoff frequency of NA/λ . $Z_m(\mathbf{u})$ is the Zernike polynomial corresponding to the m^{th} mode, and $\mathbf{k}(m)$ represents its associated coefficient. M is the number of Zernike polynomials, and its selection depends on the trade-off between aberration complexity and computational efficiency. Specifically, in our simulation studies, we employed $M=15$ to rigorously evaluate the capability of USDPC in fitting and recovering high-order aberration profiles. In contrast, for all practical live-cell and tissue experiments, M was set to 10. This configuration is justified by the fact that typical optical systems rarely introduce excessively high-order aberrations, and setting $M=10$ reduces unnecessary optimization variables and computational cost while maintaining high-fidelity phase recovery. This compact representation constrains the solution space and ensures physical interpretability.

Based on the partially coherent forward model described in Eq. (1), the predicted intensity can be generated from the network output. The training process updates network parameters via gradient descent by minimizing a hybrid loss function that combines mean squared error (MSE) with structural similarity index (SSIM) to enforce data fidelity. A total variation (TV) regularization term is further incorporated to promote spatial smoothness in the reconstructed result. The hybrid loss function is defined as

$$\begin{aligned} \mathcal{L} = & \frac{1}{4} \sum_{i=1}^4 \{ \|\mathbf{F}(a, \phi, P, S_i) - I_i\|_2^2 \\ & + \eta (1 - \text{SSIM}(\mathbf{F}(a, \phi, P, S_i), I_i)) \} \\ & + \tau \mathcal{R}_{\text{tv}}(a, \phi), \end{aligned} \quad (14)$$

where $\mathbf{F}(\cdot)$ is the forward operator computed via Eq. (1). The parameter η and τ control the strength of the SSIM and TV regularization, which affect the reconstruction accuracy and convergence efficiency. An excessively large τ introduces over-smoothing and degrades the spatial resolution, whereas an overly small τ fails to suppress discretization and pixelation artifacts. A small η reduces the contribution of the SSIM term and slows the convergence. Based on empirical evaluation, η and τ were set around 10^{-2} , which provides a good balance between reconstruction accuracy and computational efficiency for both simulations and experiments. By integrating multiple constraints within the hybrid loss function, USDPC not only achieves high-fidelity reconstruction but also significantly improves the convergence efficiency of the nonlinear optimization (see Supplementary Section 2). To further enhance computational efficiency,

mixed precision training was adopted, where computationally intensive operations were performed in FP16 precision while numerically sensitive operations were maintained in FP32 precision. Leveraging GPU Tensor Core acceleration, these strategies reduce memory consumption and increase computational throughput without compromising reconstruction accuracy. Although the neural-field framework allows the use of automatic differentiation provided by PyTorch to implicitly compute the gradients of the loss function with respect to the trainable parameters via a computational graph, thereby enabling the implementation of gradient descent optimization, we derived here the explicit update formulas to clarify the optimization process. The network parameters are updated during training via gradient descent (see Supplementary Section 1 for detailed derivation)

$$\begin{cases} \mathbf{W}_i^o = \mathbf{W}_i^o - \alpha^o \frac{\partial \mathcal{L}}{\partial \mathbf{W}_i^o} \\ \mathbf{W}_i^s = \mathbf{W}_i^s - \alpha^s \frac{\partial \mathcal{L}}{\partial \mathbf{W}_i^s} \end{cases}, \quad (15)$$

where α^o and α^s correspond to the update step size of two MLPs. $\frac{\partial \mathcal{L}}{\partial \mathbf{W}_i^o}$ and $\frac{\partial \mathcal{L}}{\partial \mathbf{W}_i^s}$ are the gradients of $\mathcal{L}$ with respect to $\mathbf{W}_i^o$ and $\mathbf{W}_i^s$, respectively. To visually demonstrate the convergence process of USDPC, a reconstruction example using HeLa cells is animated in Supplementary Video 1.

2.4 Experimental setup

The USDPC experimental platform was built on a commercial inverted microscope (IX73, Olympus, Japan), configured for bright-field imaging with programmable LED array illumination replacing the conventional halogen lamp. The LED array, with a pixel pitch of 2 mm and positioned 45 mm above the sample stage, provides quasi-monochromatic illumination centered at 507 nm. During data acquisition, four asymmetric half-circular illumination patterns (left, right, up, and down) are sequentially displayed on the LED array and switched by a field-programmable gate array (FPGA) controller (EP4CE10E22C8N, Intel, USA). The maximum illumination numerical aperture was configured to match the numerical aperture of the detection objective ($\text{NA}_{\text{ill}} = \text{NA}_{\text{obj}}$), corresponding to the optimal operating condition for partially coherent DPC imaging. Under this NA-matched configuration, the transfer function achieves its maximum effective bandwidth, extending the achievable phase resolution to the incoherent diffraction limit while maintaining sufficient low-frequency transfer for accurate quantitative phase reconstruction. The illumination beam then passes through the sample and is collected by a $10\times/0.4$ NA objective lens (UPLSAPO, Olympus, Japan). Finally, the transmitted intensity is recorded by a CCD camera (DMK 33UX226, The Imaging Source) with a pixel size of $1.85\ \mu\text{m}$. With an exposure time of 50 ms per frame, four full-frame

(3872×2764) 8-bit raw intensity images can be acquired within 200 ms. For the subsequent neural optimization, the data processing pipeline was executed on a workstation equipped with an AMD Ryzen 9 7950X3D 16-core CPU and an NVIDIA GeForce RTX 4070 Ti GPU. The computational framework was implemented in Python 3.9.25 using PyTorch 2.8.0 with CUDA 12.8 acceleration. Under this hardware configuration, the iterative reconstruction of a standard 512×512 image patch typically required approximately 10 min to reach full convergence.

3 Results

3.1 Numerical simulation verification of USDPC

To validate the high-precision QPI capability of USDPC, we performed extensive numerical simulations with representative test samples, as depicted in Fig. 2. The optical parameters employed in the simulations were matched to those utilized in the experimental setup. We first generated a complex transmission phantom consisting of a microlens-encoded phase component and an alphabet-pattern amplitude component (Fig. 2(a)). The phase modulation reached a peak value of 60 rad, far exceeding the validity range of the weak object approximation. Optical aberrations were introduced by linearly combining multiple Zernike modes. Figure 2(a) and 2(b) compare reconstructions obtained using conventional DPC and USDPC. The DPC reconstruction severely underestimated the phase, yielding a peak value of only 25 rad as a result of strong nonlinear distortions caused by the breakdown of weak object approximation under large-phase conditions. Moreover, the combined effects of nonlinearity and aberrations prevented accurate recovery of the absorption information. In contrast, USDPC accurately reconstructed both phase and absorption via joint multi-network optimization, achieving a peak phase of 60 rad consistent with the ground truth (Fig. 2(b)). Notably, the effective phase imaging range of USDPC is not limited to 60 rad. As shown in Supplementary Section 4, USDPC remains effective for low-aspect-ratio objects exhibiting phase variations up to 130 rad, substantially exceeding the recovery range of conventional DPC-based approaches. Although the simulated microlenses are not strictly confined to an infinitely thin plane, their lateral dimensions are substantially larger than their axial heights. Therefore, two-dimensional (2D) QPI can still represent the optical phase delay accumulated through the object⁶¹. Quantitative analysis further confirmed the superior reconstruction accuracy of USDPC, with the RMSE reduced from 37.42% (DPC) to 0.29% and the structural SSIM improved from 0.076 to 0.9777. In addition, the retrieved Zernike coefficients closely matched the ground truth, indicating effective decoupling between sample phase and optical aberrations.

We next evaluated the resolution performance of USDPC in the presence of optical aberrations using a standard

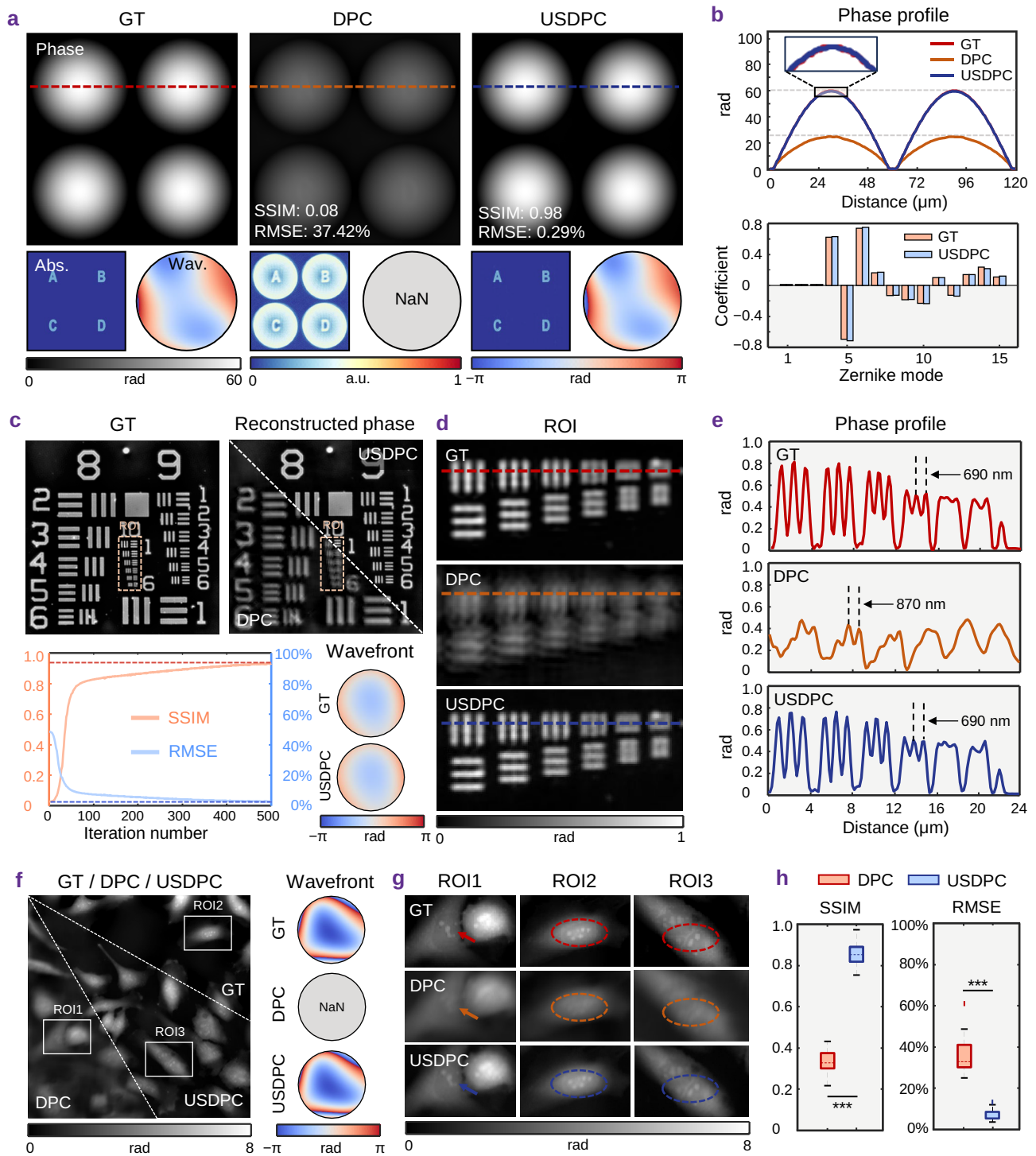


Fig. 2 | Validation of USDPC through numerical simulation. (a) Simulated optical aberration and test microlens array with an absorption distribution, along with reconstruction results obtained using conventional DPC and the proposed USDPC methods. (b) Phase line profile along the marked line in (a) and corresponding Zernike coefficients retrieved via USDPC. (c) Simulated resolution target and its reconstructions via DPC and USDPC. (d) Magnified view of ROI indicated in (c). (e) Phase line profiles extracted along the markers in (d). (f) Simulated HeLa cells sample and corresponding reconstructions using DPC and USDPC. (g) Enlarged ROIs of the regions indicated in (f). (h) Quantitative evaluation of reconstruction performance using SSIM and RMSE metrics ($n = 36$ independent ROIs). *** $p < 0.001$.

United States Air Force (USAF) phase resolution target. As shown in Fig. 2(c)–2(e), conventional DPC resolved only element 10-2, exhibiting pronounced blurring and loss of fine structural details due to aberration-induced degradation of the optical transfer function. In contrast, USDPC resolved element 10-4 by accurately compensating for optical aberration, achieving a lateral resolution of 690 nm, in agreement with the theoretical incoherent diffraction-limited resolution. USDPC also exhibited favorable convergence behavior, with SSIM values exceeding 0.85 and RMSE values below 0.1% after just 100 iterations, reaching full convergence within 500 iterations (Fig. 2(c)).

Finally, a simulated HeLa cell sample with phase modulation up to 8 rad was used to evaluate biological imaging performance (Fig. 2(f) and 2(g)). Conventional DPC failed to recover fine intracellular structures, whereas USDPC produced high-fidelity reconstructions, accurately capturing the cell morphology and subtle variations across cytoplasmic and nuclear regions. Quantitative analysis across multiple regions of interest (ROIs) further confirmed the superiority of USDPC in Fig. 2(h), with consistently higher SSIM and significantly lower RMSE values compared to DPC. These results demonstrate the robustness of USDPC in biological imaging and highlight its ability to compensate for optical aberrations and provide high-resolution, high-precision quantitative phase reconstructions. Furthermore, the capability of USDPC to compensate for high-order complex optical aberrations and its noise robustness is systematically evaluated through numerical simulations in Supplementary Section 5 and Supplementary Section 6, respectively.

3.2 Reconstruction quality characterization with standard microlens and USAF

To experimentally validate the high-precision imaging capability of the proposed USDPC method, we performed measurements using a standard microlens array and a USAF phase resolution target, as shown in Fig. 3. The microlens array, with a refractive index (RI) of 1.46, a curvature radius of 350 μm , and a pitch of 250 μm , was immersed in water (RI = 1.33). The nominal microlens height of 23 μm corresponds to a peak phase modulation of approximately 37 rad. Four intensity images were acquired under semicircular illumination from orthogonal directions (Fig. 3(a)), and the USDPC algorithm was applied to jointly reconstruct the sample phase and optical aberrations (Fig. 3(b)). During iterative reconstruction, the residual intensity error decreased below 1% after 250 iterations, while the SSIM exceeded 0.9, indicating stable and accurate convergence (Fig. 3(c)). A comparative analysis of conventional DPC, iterative DPC³⁶, and USDPC is presented in Fig. 3(d). Conventional DPC substantially underestimated the phase, yielding a peak value of approximately 10 rad, which is only about 27% of the theoretical value, primarily due to limita-

tions in weak object approximation and defocus-induced artifacts, as further evidenced by the line profile in Fig. 3(e). Although iterative DPC substantially improves the recovered peak phase through nonlinear optimization, it assumes an ideal pupil and therefore cannot compensate for unknown optical aberrations. As a result, noticeable deviations remain in the reconstructed phase distribution, particularly near the object boundaries (Fig. 3(e)). In contrast, USDPC effectively mitigated phase loss and recovered a peak phase value close to the theoretical value while accurately reconstructing the overall phase distribution.

We further experimentally evaluated the spatial resolution of USDPC using a USAF phase resolution target. The reconstructed phase maps obtained using DPC and USDPC are shown in Fig. 3(f). Due to defocus-induced aberrations, conventional DPC resolved only up to element 10-2, corresponding to a full-width spatial resolution of 870 nm. In contrast, USDPC jointly estimated the sample phase and optical aberrations (Fig. 3(g)), enabling resolution of element 10-4 with a full-width resolution of 690 nm, in agreement with the theoretical diffraction-limited resolution, as shown in Fig. 3(h) and 3(i). Pseudo-color 3D renderings of low-frequency ROI2 (Fig. 3(j)) further demonstrate that USDPC yields continuous, smooth, and structurally accurate reconstructions, whereas conventional DPC exhibits depressed artifacts and distortions arising from uncorrected aberrations. These results indicate that USDPC enables accurate, high-fidelity quantitative phase reconstructions even under non-ideal experimental conditions. The method achieves incoherent diffraction-limited resolution while maintaining robustness to optical aberrations and nonlinear effects, underscoring its suitability for high-performance imaging in practical experiments.

3.3 Wide-field imaging on stained histological section

We performed wide field-of-view (FOV) imaging of a hematoxylin and eosin (H&E)-stained kidney tissue section to evaluate the performance of USDPC on biological samples with absorption and phase variations. Each acquisition covered an area of 0.3 mm² (646.62 μm $\times$ 461.59 μm), which was partitioned into an 8 $\times$ 6 grid of subregions for localized reconstruction and correction of spatially varying optical aberrations (see Supplementary Section 7). Phase maps were successfully reconstructed with peak values reaching approximately 7 rad, establishing the ability to decode large phase information from intensity measurements, as shown in Fig. 4(a) (see also Supplementary Video 2). A magnified view of a subregion (ROI1 in Fig. 4(a)) is presented in Fig. 4(b), displaying the reconstructed phase, absorption, and aberration. The absorption images clearly resolve essential histological features, such as glomeruli, proximal convoluted tubules, and distal convoluted tubules, attributed to the high affinity of H&E staining. Notably, in regions with weak absorption contrast, such as the glomerulus-tubule

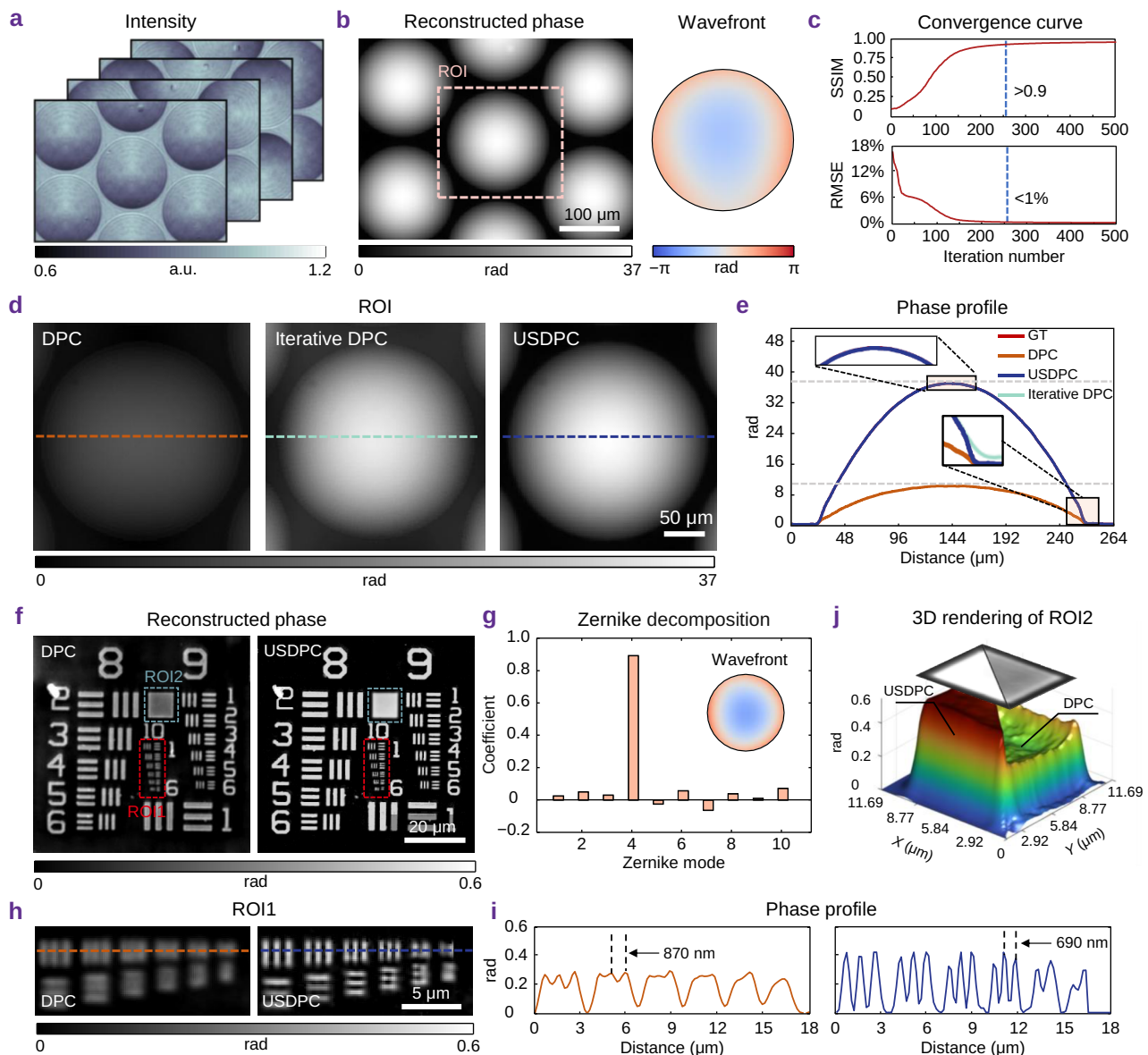


Fig. 3 | Experimental verification of the USDPC using standard microlens array and resolution target. (a) Four raw intensity images of the microlens array acquired under different illumination patterns. (b) Reconstructed phase map of the microlens array and corresponding aberration map. (c) Convergence curves of SSIM and RMSE during the reconstruction process. (d) Comparison of phase reconstructions by conventional DPC, iterative DPC, and USDPC within the ROI indicated in (b). (e) Phase line profiles extracted along the markers in (d). (f) Reconstructed phase map of the USAF target using DPC and USDPC. (g) Recovered aberration corresponding to the USAF experiment. (h) Magnified view of ROI1 in (f). (i) Phase line profiles corresponding to the markers in (h). (j) 3D rendering of ROI2 indicated in (f).

interface, the phase images provided superior structural visibility, underscoring the complementary nature of phase and absorption modalities in biological tissue characterization.

To further validate the reconstruction performance, three representative subregions (ROI2, ROI3, and ROI4) were selected to compare conventional DPC, USDPC without aberration correction (AC), and USDPC with AC (Fig. 4(c)). For the "without AC" configuration, the pupil function was fixed to an ideal aperture, and the MLP module responsible for aberration estimation was disabled. Comparative analysis reveals that the quality of phase reconstruction varied

significantly across these methods. Conventional DPC yielded low-contrast images, particularly within glomerular regions, while USDPC without AC suffered from edge blurring and loss of detail due to uncorrected aberrations. In contrast, USDPC with AC, which jointly estimated optical aberrations and object functions, significantly enhanced edge sharpness and provided more accurate delineation of tissue boundaries. These results highlight the efficacy of the USDPC framework in correcting spatially varying aberrations and achieving high-precision phase imaging across a wide FOV. Further evaluation of two additional subregions

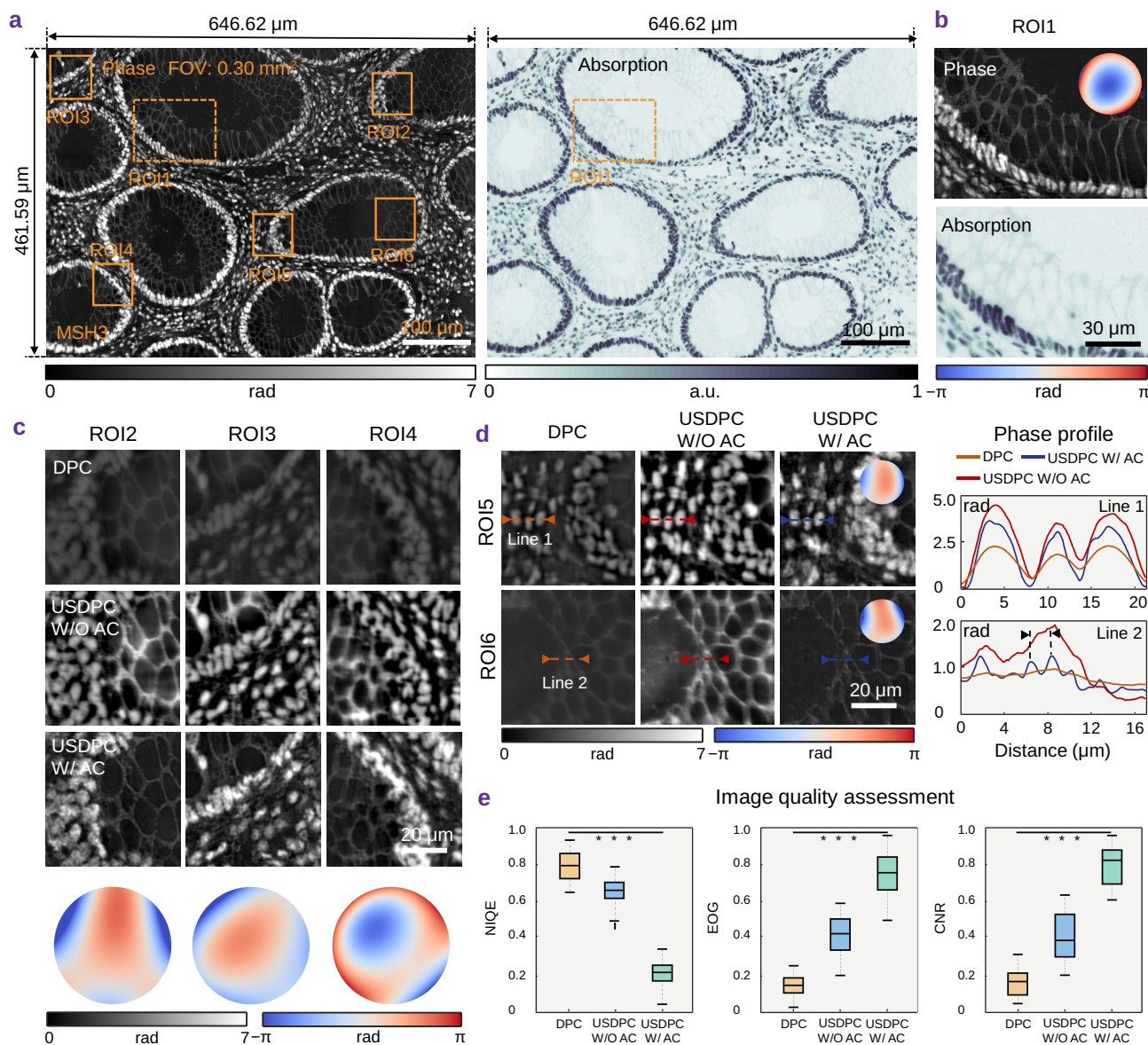


Fig. 4 | Wide-field imaging of a stained histological section using the USDPC method. (a) Reconstructed full FOV phase and absorption results (see also Supplementary Video 2). (b) Reconstructed phase, absorption, and aberration corresponding to ROI1 in (a). (c) Comparison of the reconstruction results using conventional DPC, USDPC without AC, and USDPC with AC for three representative subregions (ROI2, ROI3, and ROI4) indicated in (a). (d) Enlarged view of ROI5 and ROI6 in (a), along with phase line profiles extracted along the indicated markers. (e) Quantitative assessment of imaging quality using NIQE, EOG, and CNR metrics ($n = 48$ independent ROIs). *** $p < 0.001$.

(ROI5 and ROI6) is presented in Fig. 4(d), where extracted phase line profiles confirm the high resolution and quantitative fidelity of the proposed method. Notably, the reconstructed aberrations across these subregions reveal a clear radial dependency: the magnitude of spatially varying aberrations intensifies as the distance from the center of the FOV increases. To quantitatively assess imaging quality, the Natural Image Quality Evaluator (NIQE), Energy of Gradient (EOG), and Contrast-to-Noise Ratio (CNR) were employed as metrics (see Supplementary Section 8). As shown in Fig. 4(e), USDPC consistently achieved lower NIQE values and higher EOG and CNR values compared to alternative meth-

ods, statistically confirming its significant improvements in both visual clarity and structural detail. Supplementary Section 9 provides additional results of the unstained pathological sections, where the phase modulation has reached 20 rad, capturing more structural information beyond the reach of conventional DPC.

3.4 Long-term phase imaging of living HeLa cells

Leveraging the rapid intensity acquisition and the ability to compensate for spatially and temporally varying effective aberrations, we employed USDPC for long-term phase

imaging of living HeLa cells. Observations were conducted continuously for 5 hours to capture dynamic cellular events, including cell division and fusion. The four raw intensity images required for each frame set were acquired at 5 Hz and stored locally. Owing to the current computational cost of USDPC, the reconstruction was performed offline on selected frame sets. Figure 5(a) presents the phase maps at the initial and final time points of the reconstructed time-lapse sequence. Over the 5-hour observation period, the cell count within the FOV increased slightly from 251 to 261. The limited proliferation was attributed to the cessation of carbon dioxide supply at a later stage, which inhibited mitosis and induced cells to adopt a spherical morphology with pronounced phase contrast, as illustrated in the right inset of Fig. 5(a). Throughout the observation period, the majority of HeLa cells exhibited vibrant morphological dynamics, including contraction, extension, migration, and division. To quantify the phase imaging precision of USDPC, the reconstructed phase map at the initial time point was analyzed by fitting the background phase histogram with a Gaussian function. As shown in Fig. 5(b), the standard deviation of the fitted Gaussian yields a spatial phase precision of 3.69×10^{-3} rad. To further assess its temporal phase stability, the same background region was analyzed at selected 150 equally spaced time points spanning the entire 5-hour measurement period. The resulting phase fluctuations are summarized in the box plot in Fig. 5(c), demonstrating consistently stable quantitative phase measurements over time. Figure 5(d) compares the temporal evolution of dry mass reconstructed by conventional DPC and USDPC during the first 120 min of the 5-hour observation. USDPC yields consistently larger dry-mass estimates than conventional DPC, which is consistent with the reduced phase underestimation observed in the USDPC reconstruction.

To validate the capability of USDPC in correcting varying aberrations, two representative subregions were selected for time-lapse visualization of their reconstructed phase and estimated aberration (Fig. 5(e)). The proposed method effectively compensates for aberrations arising from sample-induced inhomogeneities, mechanical microscope drift, environmental thermal fluctuations, etc. Notably, the estimated aberration exhibited a distinctive "twin-peaked" pattern, which was primarily attributed to the inherent geometric unevenness of the petri dish bottom. In addition, we identified an abnormal multipolar division followed by a cell fusion event (Fig. 5(f)). Specifically, a single mother cell divided into three daughter cells, after which two daughter cells underwent membrane fusion to form a single intact cell. Figure 5(g) further illustrates the comprehensive morphological characterization of a mitotic process. During prophase, the cell contracts into a spherical shape characterized by elevated phase values. Subsequently, spindle forces drive cytoplasmic partitioning into two smaller daughter cells. As the cells reattach and spread, their phase values gradually decrease, and subcellular structures, such as nuclei

and vesicles, become clearly distinguishable, ultimately restoring the interphase morphology (see also Supplementary Video 3). The 3D surface renderings of the quantitative phase maps effectively capture these dynamic morphological transitions. Additional experiments further demonstrate that USDPC is applicable to higher-NA objectives, as detailed in Supplementary Section 10. These results demonstrate that USDPC enables long-term, high-precision quantitative monitoring of live-cell dynamics under the label-free acquisition and culture conditions, providing a powerful tool for investigating cellular dynamics.

4 Conclusion and discussion

In summary, we have presented a universal neural-field solver for DPC microscopy that addresses the inherent limitations of conventional DPC techniques. By embedding a partially coherent imaging model within an implicit neural-field framework, USDPC effectively performs physics-constrained, unsupervised inversion of the strict nonlinear intensity-to-phase relationship under partially coherent illumination, without relying on linearization or approximations regarding sample properties or optical parameters. The proposed framework enables accurate phase recovery beyond the weak-object regime while simultaneously self-calibrating unknown aberrations without additional calibration data or acquisition overhead. Comprehensive simulations and experimental validations, ranging from standard microlens arrays and resolution targets to complex biological tissues, demonstrate the superior reconstruction accuracy and robustness of USDPC. Although the unsupervised neural optimization framework incurs higher computational cost than conventional single-step DPC deconvolution, it provides substantially improved quantitative phase reconstruction under challenging conditions involving large phase variations, non-negligible absorption, and significant optical aberrations. By combining nonlinear phase retrieval with blind aberration correction, USDPC provides a general framework for high-accuracy quantitative phase imaging. It is worth emphasizing that the standard four-frame illumination scheme used in this study provides sufficient measurement redundancy for stable joint reconstruction of general samples. As demonstrated in Supplementary Section 11, further reducing the number of illumination frames results in significant cross-talk coupling artifacts.

Despite these encouraging results, several limitations remain and warrant further investigation. First, the current forward model explicitly accounts only for optical aberrations, whereas practical imaging systems inevitably involve additional sources of model mismatch, including illumination nonuniformity, inaccurate pupil modeling, and background or intensity normalization errors. These imperfections may violate the assumed forward imaging model and consequently degrade the reconstruction accuracy. Future work will therefore focus on improving the fidelity of the

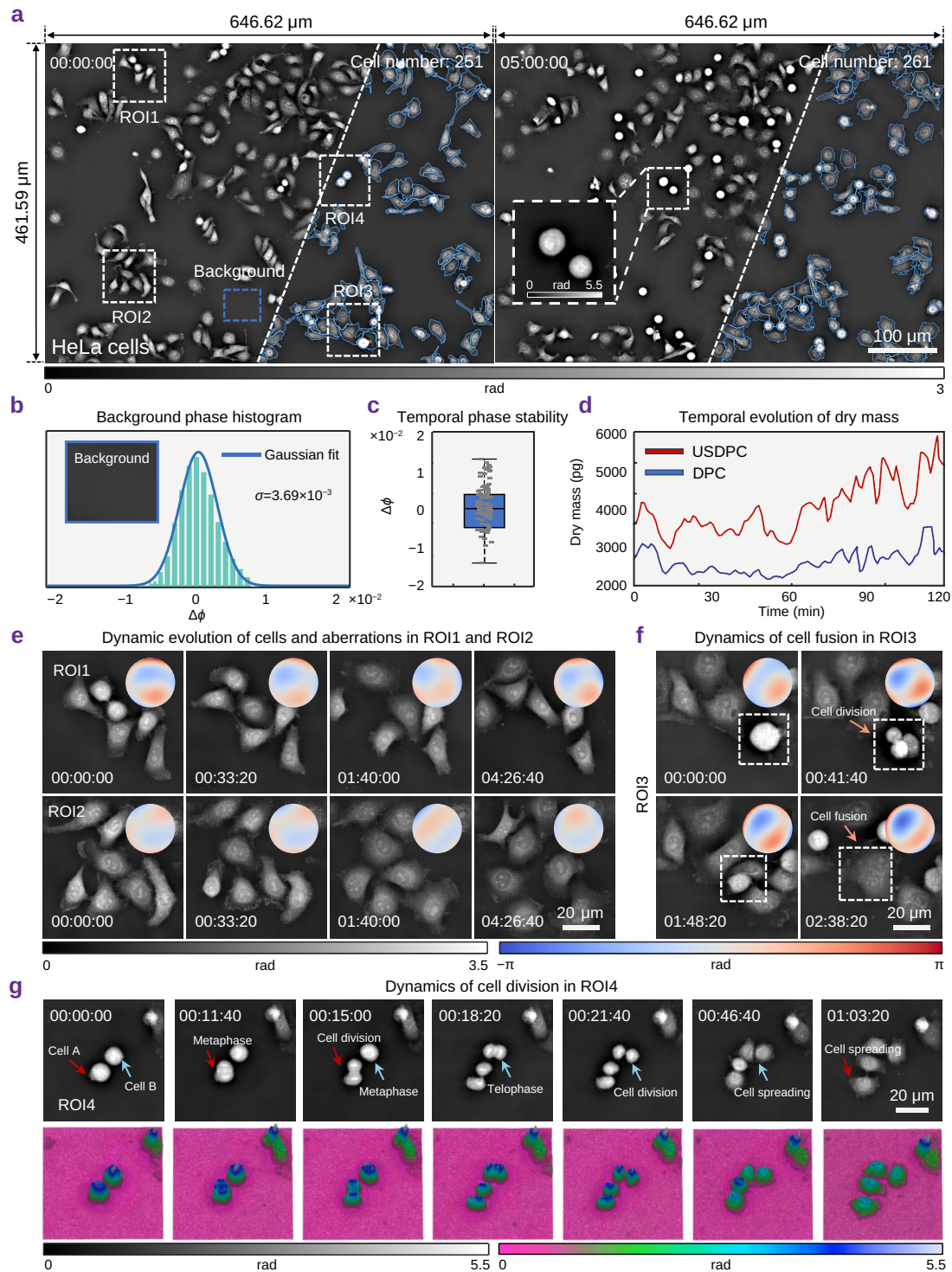


Fig. 5 | Dynamic phase imaging of living HeLa cells. (a) The first and last full-field phase images from a reconstructed time-lapse video, showing the overall changes in cell distribution and morphology during the 5-hour observation. (b) Phase histogram of the background region in the reconstructed image and the corresponding Gaussian fitting curve. The spatial phase precision estimated from the standard deviation of the background is 3.69×10^{-3} . (c) Background phase fluctuation measured at selected 150 equally spaced time points spanning the entire 5-hour observation period. (d) Comparison of the temporal dry mass curves reconstructed by conventional DPC and USDPC during the first 120 min of the 5-hour observation. (e) Temporal evolution of aberration-corrected phase reconstructions in two selected subregions (ROI1 and ROI2), highlighting cell growth and morphological changes at different time points. (f) Quantitative phase analysis of an abnormal multipolar cell division in ROI3 highlighted in (a), followed by a cell fusion event, where a single mother cell divides into three daughter cells, and the daughter cells subsequently fuse to form a single cell. (g) A complete morphological characterization of the mitotic process in ROI4 (see also Supplementary Video 3).

forward model through more accurate system characterization or by explicitly incorporating these model uncertainties into the physics-informed optimization framework, thereby further enhancing the robustness and reliability of quantitative phase reconstruction. Furthermore, the proposed USDPC framework is established upon a 2D partially coherent TCC formulation, which is appropriate for specimens that can be represented by an effective complex transmittance function. For thicker samples where the axial extent cannot be ignored, only low-aspect-ratio objects can yield reliable accumulated phase measurements under appropriate focusing⁶¹. In cases involving larger axial extent or higher aspect ratio, the finite depth of focus may distort the reconstructed complex field and topography. To overcome this limitation, extended-depth-of-focus or multifocus reconstruction can be incorporated to improve quantitative phase recovery over an enlarged axial range in the future⁶².

Finally, as advanced nonlinear inverse-problem solvers, neural fields are not limited to phase retrieval in partially coherent imaging and may be applied to a broad range of inverse problems with known or partially known forward models. Benefiting from its powerful representation capability and implicit function modeling advantages, neural fields can efficiently reconstruct target information in complex systems without relying on strict analytical priors. Beyond the DPC technique discussed in this work, neural fields have exhibited broad application potential in various advanced imaging fields, including inverse scattering imaging⁶⁰, computed tomography⁶³, and dynamic scene representation⁶⁴. With the further integration of physical priors and deep learning techniques, neural fields are expected to be extended to a wider range of scientific computing applications. This may provide a universal research paradigm for solving complex inverse problems and achieving high-precision information reconstruction across interdisciplinary domains.

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Author contributions

S. Z. and X. H. contributed equally to this work. C. Z. and S. Z. conceived the project. C. Z., Q. C., and Y. Z. supervised the research. S. Z., X. H., and Y. F. carried out the experiments and analyzed the data. S. Z., X. H., Q. Z., and C. Z. contributed to the discussion and revision of the manuscript. All authors discussed the results and contributed to writing the paper.

Competing interests

The authors declare no competing interests.

Supplementary information

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