

Photonics Breakthroughs 2025: Programmable Lensless Imaging With a Fresnel Zone Aperture

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Abstract—Optical imaging has long been dominated by conventional lens-based systems, which, despite their success, remain constrained by size, weight, and cost. Lensless imaging seeks to overcome these limitations by replacing lenses with thinner, lighter, and cheaper optical modulators and reconstructing images computationally, while facing trade-offs in image quality, artifacts, and flexibility inherent in traditional static modulation. Here, we review recent progress in lensless imaging and highlight a recent advance based on a programmable Fresnel zone aperture (FZA), termed LIP, which addresses these challenges through optimized aperture design and reconstruction strategies. By establishing an optimal parameter matching criterion and introducing an offset-FZA parallel merging strategy, LIP achieves high-quality reconstruction with reduced artifacts. Experimentally, LIP achieves a 2.5-fold resolution improvement and a 3 dB signal-to-noise-ratio gain in the static mode, while maintaining an interactive frame rate of 15 fps in the dynamic mode. We further discuss lens-based HoloFZA as an extension of programmable FZA modulation and discuss the broader significance, current limitations, and future prospects of lensless imaging toward compact, high-quality, and multifunctional visual sensing.

Index Terms—Lensless imaging, programmable Fresnel zone aperture, dynamic modulation.

I. INTRODUCTION

A. Background

THE rapid development of wearable devices, human-machine interaction, and intelligent terminals has imposed increasingly stringent demands on modern optical imaging

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systems in terms of size, cost, and imaging performance. As an important branch of computational imaging, lensless imaging eliminates the bulky lens assemblies used in conventional systems and instead introduces thin amplitude- or phase-modulating elements in front of the sensor, together with computational reconstruction algorithms to recover multidimensional optical field information. Compared with traditional optical systems, lensless imaging offers a route toward compact and potentially high-performance imaging.

Lensless imaging originated in the field of X-ray astronomy, where the fabrication of conventional lenses is highly challenging [1], [2], [3], [4]. Benefiting from its compact structure and simple optical configuration, it has subsequently found broad application in biomedical microscopy [5], [6], [7], [8], [9], [10], [11], [12] and macroscopic imaging [13], [14], [15]. By introducing a controllable optical encoding operator between the incident optical field and the sensing plane, lensless imaging encodes scene information into two-dimensional intensity measurements and subsequently recovers the target information through computational inversion [16], [17].

In recent years, this technique has been further extended to macroscopic scene perception, three-dimensional imaging, and multifunctional integration [18], giving rise to several representative modulation strategies. Early works mainly relied on fixed amplitude masks to encode scene information into intensity measurements, providing a simple route to compact imaging systems. To improve optical efficiency, subsequent studies introduced phase modulation schemes, in which the phase of incident light is modulated by designed phase masks or diffusers. Such schemes are particularly suitable for imaging in low-light scenarios and can improve the SNR of the reconstructed images. More recently, with the development of programmable modulation devices such as liquid crystal displays (LCDs) and spatial light modulators (SLMs), masks have been endowed with enhanced modulation flexibility [19], [20], [21], [22], [23]. Among these modulation strategies, the Fresnel zone aperture (FZA) [24], [25], [26], [27], [28], [29] has attracted increasing interest in programmable lensless imaging, as it offers a relatively clear analytical model and well-defined frequency response. Fig. 1 shows representative prototypes of these lensless cameras and various modulation masks.

B. Challenges

Although lensless imaging has shown substantial potential, existing techniques based on either static or dynamic

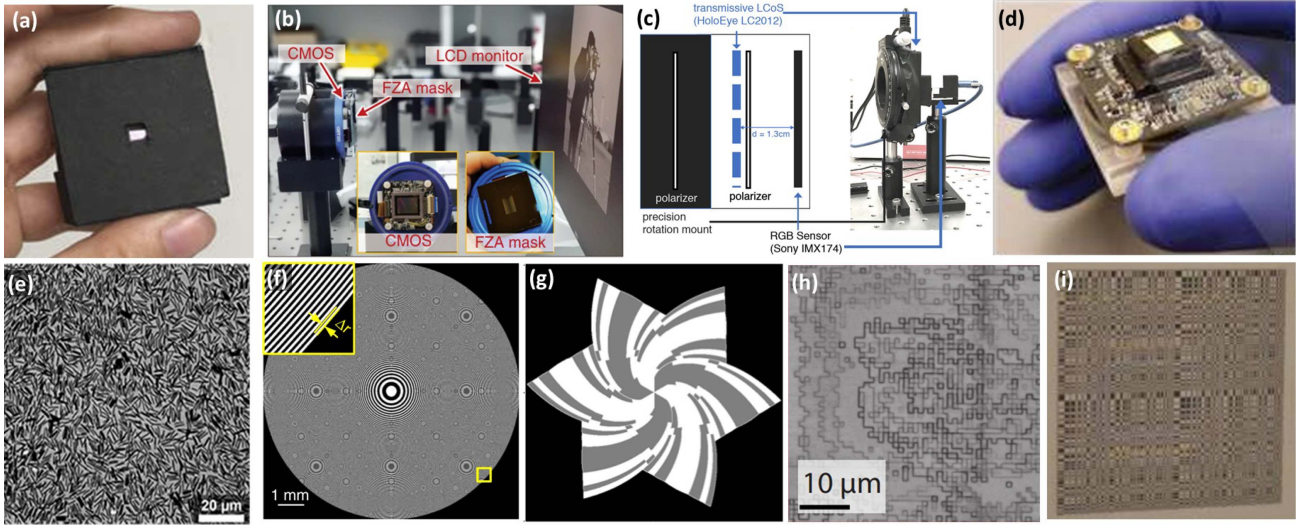


Fig. 1. (Top) Representative prototypes of lensless imaging systems. (a) On-chip fluorescence microscope with a random microlens diffuser (Figure is adapted from [30]). (b) Single-shot Fresnel zone aperture (FZA)-based lensless imaging system (Figure is adapted from [26]). (c) SweepCam system (Figure is adapted from [21]). (d) Bio-FlatScope system (Figure is adapted from [31]). (Bottom) Representative modulation masks used in lensless imaging. (e) Reconfigurable scattering mask (Figure is adapted from [32]). (f) Fixed binary-amplitude FZA used for single-shot lensless imaging (Figure is adapted from [26]). (g) Spiral phase grating (Figure is adapted from [33]). (h) Phase mask for generating a contour point spread function (PSF) (Figure is adapted from [15]). (i) Random microlens diffuser (Figure is adapted from [13]).

modulation still face a central challenge: how to stably and faithfully recover high-dimensional scene information from limited two-dimensional intensity measurements. This inverse problem is intrinsically ill-posed, and reconstruction quality depends strongly on model accuracy, noise level, and prior regularization, particularly in complex imaging scenarios. From the perspective of acquisition strategy, current lensless methods can generally be divided into single-frame and multi-frame schemes. Single-frame methods, such as the amplitude-mask-based FlatCam, the single-shot FZA camera based on a static amplitude mask, and phase-modulated systems such as PhlatCam, Bio-FlatScope, on-chip fluorescence microscopy with a random microlens diffuser, and ultra-miniature diffractive imagers, are generally more suitable for dynamic imaging than multi-frame strategies. However, the limited measurement information often makes the inverted images more susceptible to twin-image artifacts and reconstruction distortions, thereby degrading image quality, while also placing stricter demands on mask design, calibration accuracy, and reconstruction priors. By contrast, multi-frame imaging methods, such as SweepCam and lensless imagers based on reconfigurable scattering masks, constrain the solution space through multiple measurements, thereby alleviating the ill-posedness of the inverse problem and improving reconstruction quality. This, however, comes at the expense of temporal resolution and also increases the processing burden associated with image registration and computational reconstruction. In FZA-based lensless systems, while the FZA provides a clear analytical model and favorable frequency response characteristics, its performance remains jointly constrained by parameter design and sampling strategy. Parameters such as the aperture radius and fringe density of the FZA must be carefully balanced against field of view, spatial resolution, and fabrication feasibility. In addition, the flexibility of

FZA-based modulation remains limited, and high-quality reconstruction generally requires both appropriate parameter matching and multiple acquisitions under different operating conditions. Therefore, in practical applications, such systems often also face the limitations commonly associated with multi-frame imaging, including restricted temporal resolution, increased registration requirements, and higher reconstruction complexity.

Furthermore, when pixelated programmable devices such as LCDs are used to implement the FZA, device characteristics including discrete sampling, finite pixel size, and fill factor result in additional diffraction orders and periodic spectral replicas, thereby causing loss of high-frequency information. A low fringe density limits the range of spatial frequencies that can be modulated and thus constrains the achievable reconstruction resolution [26]. As the fringe density increases, the spatial variation of the FZA pattern becomes finer, until it exceeds the effective sampling capability of the display device, leading to more severe spectral aliasing and reconstruction artifacts. Therefore, the performance of programmable FZA-based imaging systems is critically determined by the trade-off between aliasing suppression and efficient use of frequency-domain information, which requires proper parameter matching under discrete sampling. These trade-offs motivate the development of a programmable encoding framework that can adapt its spatial-frequency sampling strategy to different imaging requirements.

C. Breakthroughs

Here, we review representative advances in lensless imaging, with particular emphasis on lensless imaging with a programmable Fresnel zone aperture (LIP) [34] (Fig. 2). This review summarizes the methodology and principal results of LIP, places it in the context of representative lensless imaging architectures

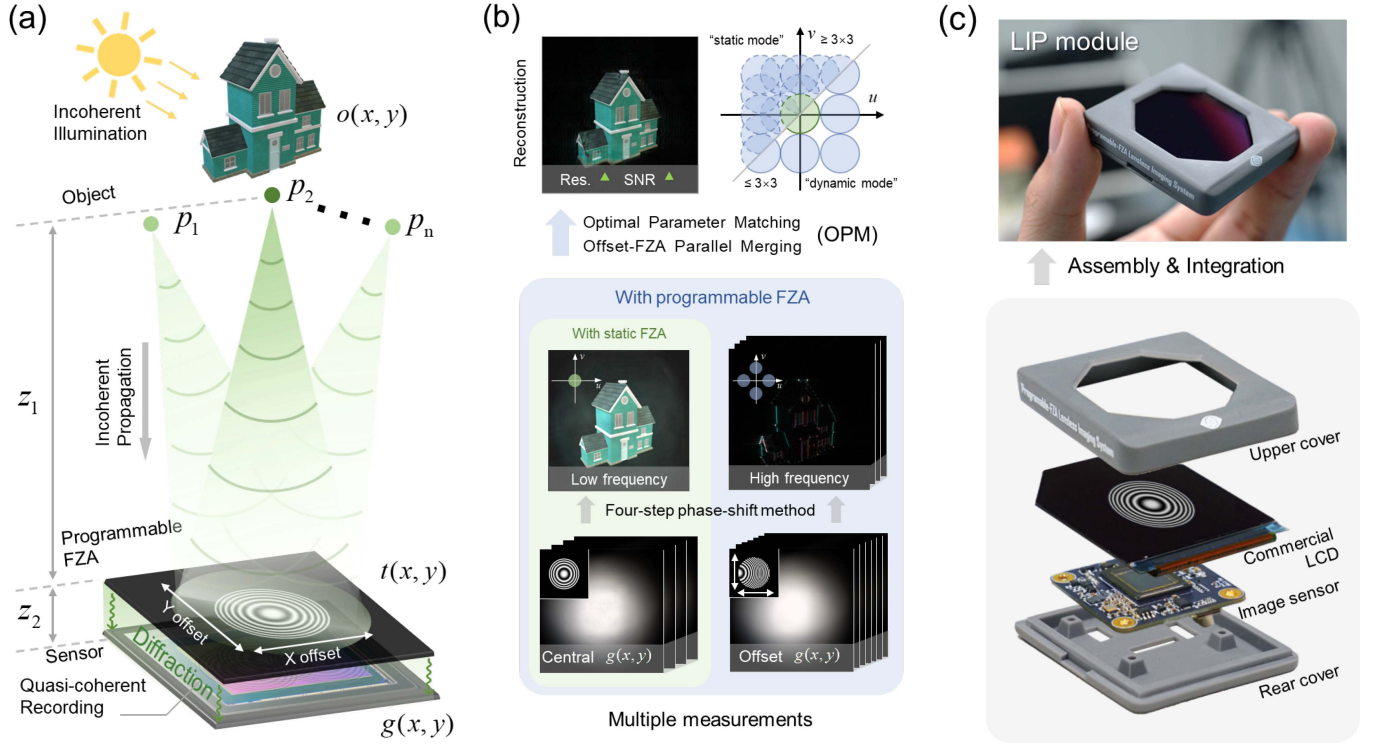


Fig. 2. Forward model of the programmable FZA-based lensless imaging system. (a) Schematic illustration of the basic principle of lensless imaging using a programmable FZA. (b) Multiple measurements and computational reconstruction based on the OPM method, where the designed adaptive mode switching includes both static and dynamic modes. (c) Integrated LIP module for the lensless imaging system. The module mainly consists of a CMOS image sensor and a commercial LCD, where the LCD provides programmable amplitude modulation. Figure is adapted from ref. [34].

through a qualitative comparison, discusses the extension of programmable FZA encoding to lens-based HoloFZA imaging, and analyzes the system-specific limitations and future directions of programmable FZA imaging. The LIP framework combines the shifted point spread function (PSF) modulation property of the FZA with a parallel frequency-domain stitching strategy to construct a programmable computational imaging framework with joint spatial- and frequency-domain optimization. This framework effectively alleviates the aliasing and artifact issues that are difficult to avoid in conventional fixed-mask schemes. Experimentally, LIP achieves a 2.5-fold improvement in spatial resolution and a 3 dB increase in SNR in the static mode. In the dynamic mode, the system maintains an interactive frame rate of 15 fps, thereby providing a practical balance between reconstruction quality and temporal efficiency.

Table I provides a structured comparison of representative mask-based lensless imaging systems in terms of modulation type, acquisition number, calibration requirement, and major advantages and limitations. FlatCam and the single-shot FZA camera both employ fixed amplitude encoders and support single-shot acquisition, but their encoding responses cannot be modified after fabrication. FlatCam relies on a calibrated system matrix or separable forward model, whereas the single-shot FZA camera uses an analytically defined binary FZA and suppresses the twin-image artifact through iterative compressive-sensing reconstruction. SweepCam also uses programmable amplitude modulation, but obtains measurement diversity through sequentially displayed coded masks for depth-aware reconstruction.

Phase-mask-based systems, such as DiffuserCam and PhlatCam, generally provide higher photon efficiency and support single-shot acquisition, but typically rely on prefabricated optical elements, system-specific PSF calibration, and fixed modulation functions. By contrast, LIP exploits the analytical shift-frequency relationship of the FZA and supports adaptive switching between multi-offset static acquisition and spatially multiplexed dynamic acquisition. Therefore, LIP combines analytically tractable encoding with programmable spectral coverage and reconfigurable static and dynamic operation, while requiring additional phase-shifted measurements and remaining subject to LCD-induced sampling constraints, optical loss, and geometric and temporal calibration errors.

Beyond the lensless LIP framework, the programmable FZA encoding principle can also be extended to lens-based incoherent holographic imaging. This related configuration, termed HoloFZA, uses an FZA for beam-splitting and phase-shifted self-interference recording. Its relationship with LIP and the corresponding experimental results are discussed in Section II-D.

II. BREAKTHROUGH RESEARCH

A. Concept and Forward Model

The programmable FZA-based lensless imaging system mainly consists of a commercial LCD used to display the FZA for amplitude modulation and an image sensor (Fig. 2(c)). Under incoherent illumination, each object point is projected onto the sensor plane as a distinct FZA pattern corresponding to the

TABLE I
COMPARISON OF REPRESENTATIVE MASK-BASED LENSLESS IMAGING SYSTEMS

System	Modulation type	Modulation scheme	Number of measurements	Calibration requirement	Hardware profile	Main advantages	Main limitations
FlatCam [13]	Fixed separable amplitude mask	Amplitude modulation	Single-shot	System-matrix calibration	Fixed mask–sensor architecture	Single-shot; thin architecture; scalable calibration and reconstruction	Fixed encoding; photon loss; calibration and model-mismatch sensitivity
DiffuserCam [14]	Fixed random phase diffuser	Phase modulation	Single-shot	Depth-dependent PSF calibration	Compact diffuser–sensor architecture	Single-shot 3D imaging; compact architecture; higher photon efficiency	Depth-dependent calibration; sparsity dependence
PhlatCam [15]	Fixed optimized phase mask	Phase modulation	Single-shot	System-specific PSF calibration	Phase-mask–sensor architecture	Single-shot; thin architecture; designable PSF; higher photon efficiency	Fixed encoding; calibration dependence
SweepCam [21]	Sequential programmable amplitude masks	Amplitude modulation	Multiple sequential measurements	Mask- and depth-dependent calibration	Programmable-mask system	Depth-aware imaging; large-depth-range recovery	Sequential acquisition; motion sensitivity; increased acquisition burden
Single-shot FZA camera [26]	Fixed binary-amplitude FZA	Amplitude modulation	Single-shot	No empirical PSF calibration	Fixed FZA–sensor architecture	Single-shot; compact architecture; interpretable forward model	Fixed parameters; photon loss; iterative reconstruction and sampling limits
LIP [34]	Programmable offset or multiplexed amplitude FZAs	Amplitude modulation	Static mode: $100(5 \times 5 \times 4)$ or $324(9 \times 9 \times 4)$; dynamic mode: 4	No empirical PSF calibration	Programmable LCD–sensor architecture	Static–dynamic switching; improved resolution and SNR	Multi-frame static acquisition; LCD bandwidth and efficiency limits

magnification of the programmable FZA (Fig. 2(a)). Owing to the shift-invariant property of the system, the image $g(x, y)$ recorded by the sensor is a linear superposition of the projected FZA patterns. As a bridge between incoherent imaging and coherent holography, the FZA enables incoherent point sources to be recorded in a quasi-coherent form [24], [26], [35]. Unlike ideal continuous aperture modulation, the discrete sampling structure of the LCD causes the system transfer function to be periodically replicated in the frequency domain with periods $[1/\Delta x, 1/\Delta y]$, where the pixel pitches Δx and Δy determine the spacing between adjacent spectrum replicas. Meanwhile, the finite pixel opening sizes a_x and a_y introduce an envelope term $\text{sinc}(a_x f_x) \cdot \text{sinc}(a_y f_y)$, which further constrains the effective high-frequency response of the system.

In this system, when the ideal FZA pattern to be displayed is denoted as $t(x, y)$, the actual sampled pattern on the LCD can be expressed as

$$t_s(x, y) = \left[\text{rect}\left(\frac{x}{a_x}\right) \text{rect}\left(\frac{y}{a_y}\right) \right] * \left[\text{comb}\left(\frac{x}{\Delta x}\right) \text{comb}\left(\frac{y}{\Delta y}\right) t(x, y) \right], \quad (1)$$

$$t(x, y) = \frac{1}{2} \{ 1 + \cos [\beta (x^2 + y^2) + \phi] \}, \quad (2)$$

where β is the Fresnel parameter and ϕ is the initial phase of the fringe pattern. These two parameters control the fringe density and fringe phase of the FZA, respectively. The aperture radius of the FZA is denoted by R , which affects the angular field of view of the system. The parameter β directly determines the spatial frequency range that can be encoded by the system.

Although a larger β enhances the imaging resolution, under discrete sampling it also causes the replicated spectra to expand. Once the replicated spectra begin to overlap with the central spectrum, unwanted frequency components gradually mix into the affected region, resulting in disordered phase information. Therefore, the aliasing threshold is jointly determined by the spacing between spectrum replicas and the effective support of each individual spectrum. The former is governed by the pixel pitch, whereas the latter is constrained by the pixel opening size. In other words, the upper performance limit of the system is not determined by β alone, but by whether β and R are properly matched to the discrete sampling constraints of the LCD.

B. Optimal Parameter Matching and Offset-FZA Parallel Merging

To address the sampling-induced aliasing of programmable FZA modulation, the LIP framework employs an optimal parameter matching and offset-FZA parallel merging method (OPM), as illustrated in Fig. 3. OPM first determines the appropriate aperture radius and Fresnel parameter under the geometric and sampling constraints of the system, and subsequently synthesizes the complementary spectral information acquired using multiple offset FZAs.

First, the aperture radius R is selected to ensure a large angular field of view and complete sampling of the projected FZA pattern, while maintaining the highest possible optical efficiency. Following ref. [34], the admissible range is $0 < R \leq R_m$, where the optimal aperture radius is analytically determined as

$$R_m = \frac{W/2 - z_2 \tan \theta_y}{m}, \quad (3)$$

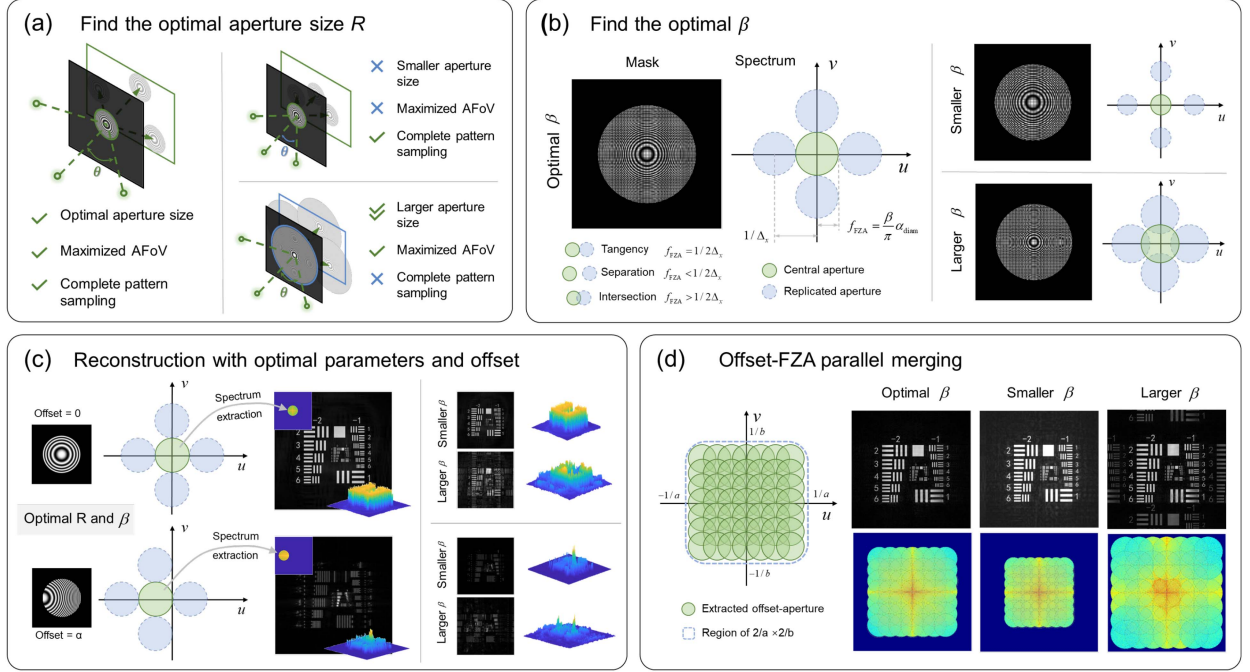


Fig. 3. Optimal parameter matching and offset-FZA parallel merging (OPM) for lensless imaging with programmable FZAs. (a) Determination of the optimal aperture radius R . A larger aperture radius improves optical efficiency while ensuring the maximum angular field of view (AFOV) and complete pattern sampling. (b) Determination of the optimal β . A carefully selected β allows the recovery of subaperture spectrum information without aliasing. (c) Reconstruction using the optimal parameters and offset operations. With the optimal parameter set, the information acquired from each subaperture through shifted FZAs can be reconstructed with high quality. (d) Offset-FZA parallel merging. By integrating all subaperture information in the frequency domain, high-quality lensless reconstruction is achieved. Figure is adapted from ref. [34].

where W is the effective sensor width, z_2 is the mask-to-sensor distance, θ_y is the viewing angle of the LCD, and m is the system magnification. For the reported LIP module, the resulting aperture radius is $R_m = 2.72$ mm.

Second, the Fresnel parameter β is selected to be as large as possible without causing overlap between the periodically replicated spectra introduced by LCD sampling. A larger β provides broader spectral coverage, whereas an excessively large value leads to spectral aliasing. The admissible range is therefore $0 < \beta \leq \beta_m$, where the largest aliasing-free Fresnel parameter is

$$\beta_m = \frac{\pi m}{2\Delta y R_m}, \quad (4)$$

and Δy is the LCD pixel pitch. For the reported system, $\beta_m = 24.24$ rad/mm². Therefore, both R_m and β_m are analytically determined from the system geometry and LCD sampling characteristics rather than empirically selected.

Third, with the optimal parameters determined, offset FZA patterns are introduced to acquire complementary aliasing-free subaperture spectra. In the spatial domain, an FZA displacement of α corresponds to a spectral displacement of $\beta\alpha/\pi$. In the static mode, adjacent spectral subapertures were designed with an overlap ratio of approximately 39.1%, providing the redundancy required for cophasing and iterative spectrum synthesis. In the static resolution experiment, a 9×9 array of offset positions with a step size of 40 LCD pixels was used. For the other

static-scene experiments, a 5×5 array was adopted to reduce the acquisition time.

For each offset position (i, j) , four FZA patterns with phase shifts

$$\phi_q = \frac{q\pi}{2}, \quad q = 0, 1, 2, 3, \quad (5)$$

are sequentially displayed. The corresponding intensity measurements $g_{i,j}^{(q)}(x, y)$ are demodulated using the four-step phase-shifting method:

$$H_{i,j}(x, y) = \sum_{q=0}^3 g_{i,j}^{(q)}(x, y) \exp\left(-i\frac{q\pi}{2}\right). \quad (6)$$

This operation recovers the complex-amplitude information associated with each subaperture while suppressing the DC and twin-image terms.

Following phase-shifting demodulation, a spectral support constraint $P_{i,j}(u, v)$ is applied to each recovered complex field to retain its aliasing-free subaperture information. The spectrum obtained from the non-offset central FZA is used as the initial estimate of the global target spectrum. At the k th iteration, the sub-spectrum corresponding to each offset position is extracted from the current global estimate and transformed into the spatial domain. The measured magnitude is then imposed while retaining the estimated phase, yielding the updated subaperture field $u_{i,j}^{(k)}(x, y)$.

Following the difference-map-inspired parallel merging strategy, all updated subaperture spectra are combined using support-normalized weighting:

$$\tilde{U}^{(k)}(u, v) = \frac{\sum_{i,j} P_{i,j}(u, v) \mathcal{F} \left\{ u_{i,j}^{(k)}(x, y) \right\}}{\sum_{i,j} P_{i,j}(u, v) + \delta}, \quad (7)$$

where $\mathcal{F}$ denotes the Fourier transform and δ is a small numerical constant introduced to avoid division by zero. Thus, frequency components covered by multiple subapertures are averaged according to their spectral-support overlap, whereas components covered by only one subaperture retain the corresponding updated value.

The global spectrum is subsequently updated using an adaptive relaxation factor:

$$U^{(k)}(u, v) = (1 - \eta_k) U^{(k-1)}(u, v) + \eta_k \tilde{U}^{(k)}(u, v), \quad (8)$$

where η_k controls the update rate. The relaxation factor was initialized as $\eta_0 = 1$ and reduced by half when the relative decrease in the data-consistency error between successive iterations was less than 1%. The reconstruction was terminated when $\eta_k < 10^{-3}$ or when the maximum number of iterations, $N_{\max} = 10$, was reached. The final object intensity and phase were obtained by applying an inverse Fourier transform to the converged global spectrum.

In the dynamic mode, nine nonoverlapping subapertures are spatially multiplexed in a 3×3 arrangement and simultaneously recovered from four phase-shifted measurements for each output frame. Their complex spectra are placed at the corresponding frequency-domain positions and synthesized through a single non-iterative merging operation, followed by an inverse Fourier transform. Therefore, the iterative update and convergence procedure described above are applied only to the high-quality static mode, whereas the dynamic mode uses direct spectrum synthesis to balance reconstruction quality and temporal efficiency.

C. Performance Evaluation in Static and Dynamic Modes

The imaging resolution of the LIP module was experimentally evaluated in the static mode, as shown in Fig. 4. A USAF resolution target was displayed on a monitor 200 mm away from the imaging system with an actual physical size of 290 mm by 290 mm. Three sets of resolution experiments were performed separately. The central aperture was imaged using the traditional FZA-based method with the optimal β obtained from the previously calculated optimal parameter matching. The overall imaging quality was fair, with no discernible aliasing. However, the relative resolution remained limited, resolving only up to the line pairs in group -1 , element 3, with an SNR of 6.38 dB. Upon increasing β , an enhancement in resolution was observed, enabling the line pairs in group 0, element 4 to be distinguished under the equivalent β condition. However, this came at the expense of image quality, as obvious aliasing artifacts appeared in the reconstructed results and the SNR decreased to 3.63 dB. In contrast, by introducing an FZA offset with a step size of

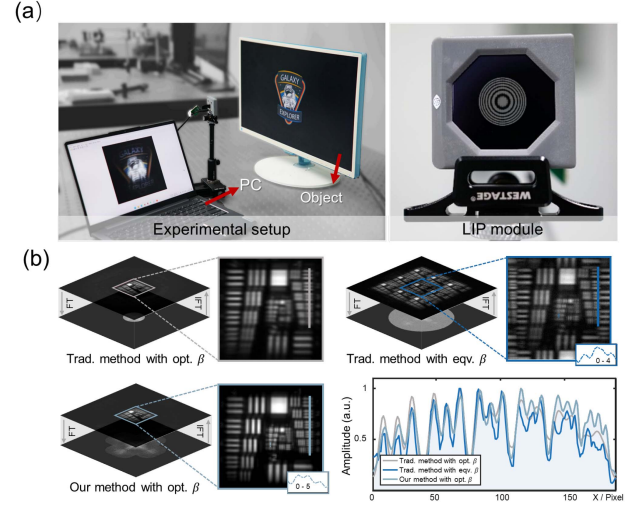


Fig. 4. Performance evaluation of the LIP module in the static mode. (a) Experimental setup. During imaging, the FZA pattern is varied with a prescribed offset step and phase shift. (b) Resolution test results using a USAF resolution target, comparing the conventional method with the optimal β , the conventional method with an equivalent β , and the OPM method with the optimal β . Figure is adapted from ref. [34].

40 pixels based on the optimal parameter matching and combining it with the OPM method using a 9×9 offset-aperture configuration, imaging quality surpassing that obtained under the equivalent β condition was achieved. The improvement is evident in the smoother and more distinguishable line-pair profiles of group -1 . Moreover, OPM allows the differentiation of group 0, element 5, which is challenging to distinguish using either the equivalent β or the traditional method, while maintaining a high SNR of 6.65 dB. Consistent with these experimental observations, numerical evaluations on ten complex objects using the corresponding ground-truth images as references showed that, compared with traditional FZA reconstruction using an equivalent β , OPM achieved average improvements of 10.2 dB in peak signal-to-noise ratio (PSNR) and 0.39 in correlation coefficient (CC). These results demonstrate that OPM improves both the recoverable spatial resolution and reconstruction fidelity while effectively suppressing sampling-induced aliasing artifacts.

By contrast, the dynamic mode of the LIP module is designed to balance reconstruction quality and imaging speed. The LCD used in the LIP module has a maximum refresh rate of 120 Hz and was operated at 60 Hz in the reported dynamic experiments. For each reconstructed frame, four phase-shifted FZA patterns were sequentially displayed and synchronously captured, while a 3×3 spatial-multiplexing configuration was used to simultaneously encode the spectral information of nine subapertures. The sensor exposure time and gain were set to 10 ms and 6 dB, respectively, and the LCD and image sensor were synchronized using a self-developed triggering circuit. Computational reconstruction was performed on a workstation equipped with an NVIDIA GeForce RTX 5090 GPU. The four measurements were reconstructed using non-iterative frequency-domain synthesis followed by an inverse Fourier transform. Taking the pattern display, image acquisition, computational reconstruction, and result display into account, the complete imaging pipeline

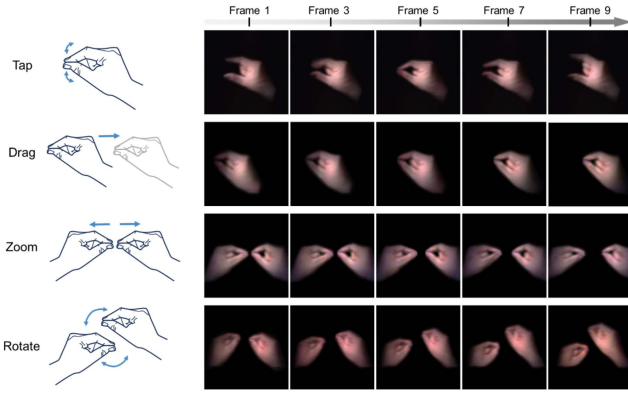


Fig. 5. Imaging results of the LIP module in the dynamic mode, showing continuous imaging results for four common interactive gestures in virtual reality (VR) devices, namely tap, drag, zoom, and rotate. Figure is adapted from ref. [34].

achieved an end-to-end frame rate of 15 fps. The application of the LIP module in hand gesture sensing and its potential for future integration into VR headsets were further demonstrated, as shown in Fig. 5. Following common interactive gestures in VR devices, four groups of gestures, namely Tap, Drag, Zoom, and Rotate, were designed for evaluation. The results show that the integrated LIP module can accurately image and capture these hand gestures, ensuring that subsequent hand key-point detection can be carried out smoothly. These results highlight the potential of the programmable FZA-based lensless imaging framework for lightweight interactive imaging and broader multimode lensless applications.

D. Extension to Lens-Based HoloFZA Imaging

Beyond the lensless configuration of LIP, programmable FZA encoding can also be incorporated into a lens-based incoherent imaging system, forming the HoloFZA architecture shown in Fig. 6. The HoloFZA results discussed in this section have not been published in a separate original research article. In this configuration, the programmable FZA is placed adjacent to the lens and divides the incident field into zero-order, converging, and diverging components. Their self-interference is recorded through four phase-shifted measurements, from which the complex-amplitude information of the object field can be recovered. Unlike conventional incoherent imaging, whose optical transfer function gradually attenuates toward high spatial frequencies, HoloFZA uses FZA-based holographic encoding to enhance the transfer of high-frequency information within the 2NA diffraction-limited passband. The uncoded image exhibits relatively low contrast in the high-frequency line pairs of the USAF target. Lucy–Richardson deconvolution improves the visibility of these details when an appropriate parameter is selected, but remains sensitive to parameter mismatch and introduces ring-shaped spectral artifacts. In comparison, HoloFZA clearly resolves the line pairs in group -1, provides higher line-profile contrast, and produces a more uniformly distributed spectrum with fewer reconstruction artifacts. Although HoloFZA is not part of the lensless LIP architecture, the two systems share the same underlying principles of programmable FZA encoding and

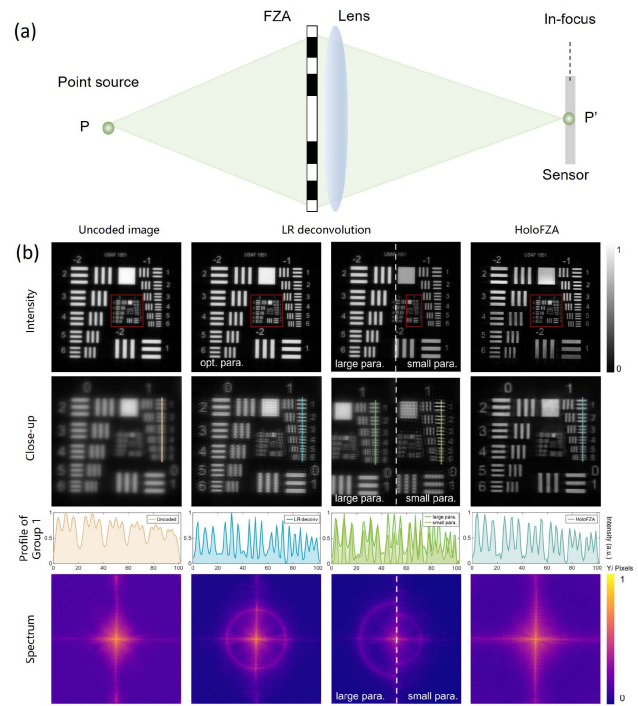


Fig. 6. (a) Schematic of the lens-based HoloFZA system. A programmable FZA is placed immediately in front of the lens, and phase-shifted measurements are used to recover the complex amplitude of the object field under passive incoherent illumination. (b) Experimental comparison on a USAF target. From left to right: uncoded image, Lucy–Richardson deconvolution with the optimal parameter, Lucy–Richardson deconvolution with mismatched parameters, and HoloFZA reconstruction. The corresponding intensity images, enlarged views, line profiles, and spectra are shown. HoloFZA provides clearer high-frequency details and reduced reconstruction artifacts.

phase-shifted complex-field recovery. LIP exploits FZA offsets to synthesize complementary spectral subapertures in a lensless system, whereas HoloFZA extends the same encoding concept to lens-based incoherent holography for high-frequency transfer enhancement and defocus-robust reconstruction. HoloFZA is therefore presented as a related extension that illustrates the broader applicability of programmable FZA modulation.

III. DISCUSSION AND PERSPECTIVES

A. Impact

As an important branch of computational imaging, lensless imaging [26], [27], [36], [37] removes the lens from the optical system and instead employs masks or other modulation elements to encode the optical field, thereby converting the high-level light field information into measured intensity distributions and recovering the target optical field through physical modeling and numerical inversion. In this way, it relaxes the size and weight [6], [13], [15] constraints imposed by conventional optical imaging systems and prompts a reexamination of the fundamental processes of image formation and information transfer. The main advantages of lensless imaging lie in its compact optical configuration, reduced hardware complexity, and adaptability to different imaging tasks through reconfigurable optical modulation [20], [21]. In addition to lowering the cost associated

with lens design and fabrication, this paradigm also provides a feasible framework for high-resolution and multimodal imaging through flexible modulation strategies [6], [14], [22], [38], [39], thereby broadening its applicability across diverse imaging scenarios.

B. Limitations

Lensless imaging is fundamentally governed by an ill-posed inverse problem, in which the object information must be inferred from a limited set of intensity measurements [17], [40]. Reconstruction performance therefore depends strongly on the accuracy of the forward model, the validity of the imposed priors, and the robustness of the inversion algorithm [41], [42]. Beyond these general constraints, the practical performance of LIP is primarily limited by the discrete spatial sampling and low optical efficiency of the programmable LCD, calibration errors in frequency-domain spectrum synthesis, and the temporal inconsistency associated with multi-frame acquisition. These limitations collectively determine the attainable resolution, reconstruction fidelity, photon efficiency, and dynamic imaging capability of the current system. First, the achievable resolution is constrained by the discrete sampling characteristics of the LCD. Increasing the Fresnel parameter β expands the recoverable spatial-frequency range, but also enlarges the periodically replicated spectra caused by pixelated sampling. Once these replicas overlap with the central spectrum, high-frequency information is mixed with aliasing components, resulting in reconstruction artifacts and SNR degradation [43], [44]. Consequently, the resolution enhancement of LIP is bounded by the LCD pixel pitch, finite pixel aperture, fill factor, and the parameter matching between β and the aperture radius R . Second, the OPM strategy relies on accurate geometric and temporal calibration. Because the frequency-domain positions of the subapertures are determined by the programmed FZA offsets, errors in LCD-CMOS alignment, system magnification, mask-to-sensor distance, offset step, or synchronization can lead to inaccurate spectrum stitching and unstable reconstruction [41], [44]. System drift and other hardware nonidealities may further increase the mismatch between the physical system and the assumed forward model. Third, the high-quality static mode requires multiple phase-shifted and offset measurements, which limits its applicability to rapidly changing scenes. Although the dynamic mode improves temporal efficiency through spatial multiplexing, it involves an inherent trade-off among the number of encoded subapertures, exposure time, reconstruction quality, and frame rate. Its performance therefore remains sensitive to scene motion and illumination variations. Finally, the polarizers, liquid-crystal layers, and finite fill factor of the amplitude-modulating LCD introduce substantial optical loss, reducing the available photon budget and making LIP more vulnerable under low-light and short-exposure conditions.

Overall, the commercial amplitude-modulating LCD constitutes the dominant hardware bottleneck of the current LIP prototype: its discrete pixel structure limits the maximum recoverable spatial-frequency range and achievable resolution, while its limited optical efficiency degrades the reconstruction SNR. Future

improvements in pixel pitch, fill factor, optical transmittance, and modulation response will therefore be critical for enhancing the resolution, SNR, and dynamic imaging performance of LIP.

C. Future Vision

With the rapid development of micro/nano-optical devices featuring high resolution and high fill factors, future front-end encoders are expected to evolve from conventional amplitude-type LCDs toward phase-only SLMs and even electrically tunable metasurfaces [20], [45], [46]. Relative to amplitude modulation, phase-based and metasurface-based platforms offer finer control over the optical field and higher photon efficiency, which is beneficial for improving modulation precision and reducing light loss in photon-limited conditions. Meanwhile, the integration of physical modeling and learning-based optimization is reshaping the design of optical encoding strategies, shifting the emphasis from predefined modulation patterns and regular scanning procedures toward encoding schemes that are optimized jointly with the reconstruction process [22], [38]. Under this framework, optical modulation and computational inversion are no longer designed separately, but are incorporated into a unified optimization pipeline. This development is gradually changing the role of reconstruction algorithms from model-based iterative solvers toward learned inference models that operate directly on physically encoded measurements, thereby improving reconstruction speed and reducing the number of required acquisitions [38]. Future lensless systems may evolve from two-dimensional intensity reconstruction toward the joint recovery of multiple physical dimensions, including depth, phase, spectral information, polarization, and temporal dynamics [39], [47]. Such a development would broaden the role of lensless computational imaging from image formation alone to multidimensional optical sensing, particularly in scenarios where system compactness and measurement diversity are both required [34].

IV. CONCLUSION

In summary, programmable Fresnel zone aperture imaging offers a practical framework for compact and reconfigurable lensless imaging. By integrating optimal parameter matching with offset-FZA parallel merging, LIP reduces sampling-induced aliasing and reconstruction artifacts while improving spatial resolution, signal fidelity, and temporal flexibility within a simple hardware configuration. These results suggest that programmable FZA systems can serve as both a versatile experimental platform and a viable framework for compact imaging applications. Looking forward, further advances in high-efficiency modulators, inverse solvers, and task-oriented optical-computational design may further push lensless imaging toward real-time, multidimensional, and application-driven systems.

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