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High-fidelity and ultra low-sampling-rate single-pixel imaging with physically enhanced Laguerre-Gaussian encoding

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Abstract: Single-pixel imaging (SPI) has offered an unprecedented technique for capturing a targeted scenes without requiring raster scanning or multi-pixel detector arrays. Despite its advantages, achieving both high spatial fidelity and ultra-low sampling ratio, particularly below 5%, without additional post-processing algorithms in the existing SPI architectures remains a significant challenge due to that a reconstruction needs a large amount of measurements. To circumvent these challenges, here we demonstrate a novel Laguerre-Gaussian single-pixel imaging (LGSPI) framework achieving ultra-low sampling ratio of 3% and super-high spatial imaging fidelity with average structural similarity (SSIM) of 0.770 and average peak signal-to-noise ratio (PSNR) of 19.140 dB. The fundamental methodology relies on the enhancement of the encoded patterns by discrete orthogonal physical Laguerre-Gaussian (LG) moments in which the measured signals have a higher compression sampling as the dimensionality of the coding LG moments increases. Leveraging this orthogonal mechanism, LGSPI demonstrates superior imaging fidelity and computational efficiency, surpassing the capabilities of non-orthogonal moments. Comparative analyses of the power spectra from reconstructed images highlight the enhanced efficacy of LGSPI over Hadamard SPI (HSI) and Fourier SPI (FSI). Our results suggest the possibility of encoding multi-dimensional structured light fields as a promising pathway for realizing low sampling ratio, universal, and physical-endow SPI.

Keywords: single-pixel imaging; Laguerre-Gaussian moment; low sampling ratio; physical coding pattern

Introduction

Single-pixel imaging (SPI)^{1–3} is a computational imaging technique that reconstructs images of a target scene utilizing a single-point detector and spatial light modulation, eliminating the need for pixelated detectors typically employed in conventional array camera system, such as those found in charge-coupled device (CCD) or complementary metal-oxide semiconductor (CMOS) sensor arrays. In SPI, a sequence of structured illumination patterns is projected onto the target scene, and the corresponding total light intensity, captured by a non-spatially resolved (bucket) detector, is recorded. The spatial information is subse-

quently retrieved through computational algorithms that correlate the known patterns with the measured signals.

In contrast to arrayed detectors, single-pixel detectors, such as avalanche diodes and photo multiplier tubes, demonstrate enhanced detection sensitivity under low-light conditions⁴. Moreover, the SPI technique offers significant potential for application in non-visible^{5–8}, multispectral imaging^{9,10}, fluorescence lifetime imaging¹¹, complex-amplitude retrieval¹², remote sensing imaging¹³, imaging through scattering media^{14,15} and optical encryption^{16,17}. However, SPI faces several challenges, including the difficulty of achieving high-fidelity, crosstalk-free, imaging at low sampling ratios. Developing new methods to simultane-

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ously address these challenges is imminent.

While SPI offers distinct advantages in computational imaging, it necessitates the use of a considerable number of illumination patterns for modulation. Early implementation of SPI employed random patterns¹⁸ necessitating extensive oversampling to achieve acceptable image fidelity. Such redundancy leads to inefficiencies in both acquisition time and reconstruction fidelity. To enhance these limitations simultaneously, recent advances in SPI have focused on two complementary strategies: algorithmic optimization and physical encoding. These approaches aim to reduce the number of required patterns while maintaining or enhancing image fidelity, thereby improving both efficiency and practicality.

In the context of algorithmic methods of SPI, compressive sensing (CS)^{3,19–21} theory has been widely adopted to reduce the total number of required measurements, enabling image reconstruction in circumstances where sampling is incomplete. Nevertheless, achieving higher compression ratios without compromising image fidelity remains challenging, as the sparsity of coefficients diminishes, necessitating a trade-off between speed and quality. The incorporation of deep learning into SPI^{22–25} has shown promise in reducing sampling ratio. Neural networks can infer complex spatial correlations from limited data, offering improved reconstruction at reduced sampling rates. However, deep learning methods are often hindered by critical limitations: lack of physical interpretability, dependence on large and diverse training datasets, and reconstruction instability arising from variations in network weights and training iterations.

In contrast, physical-based methods in SPI avoid the uncertainties associated with iterative algorithms by introducing physical mechanisms for generating the basis of SPI. These methods efficiently utilize light-intensity information with orthogonal moments²⁶ being widely applied for high efficiency image reconstruction. Notable examples include Hadamard SPI (HSI)^{15,27–29} and Fourier SPI (FSI)^{30–32}. However, cumbersome HSI needs to employ sorting algorithms^{28,33,34}, which reduce the sampling ratio in terms of compression perception. Furthermore, the ideal step-function patterns used in HSI exhibit infinite bandwidth, leading to image degradation under finite optical bandwidth and diffraction-limited conditions^{35,36}. Similarly, the use of the FSI method necessitates the introduction of a phase shift, which imposes constraints on imaging speed.

Physically enhanced orthogonal moments for single-pixel imaging

Physically enhanced orthogonal moments^{35,37–39} have great potential in advancing SPI technology by providing efficient and deterministic modulation scheme, representing a key focus and challenge in the field. However, research in this area is still in its early stages. Here, we propose a novel coding approach based on physically orthogonal Laguerre-

Gaussian (LG) moments calculated from LG function. The encoding of basis pattern is implemented in two dimensions in SPI imaging systems, enabling the image reconstruction from known LG patterns and the correlated intensity obtained from a single pixel detector. The results of the simulations and experiments consistently demonstrate that the proposed LG-based SPI (LGSPI) scheme is capable of reconstructing images of high spatial fidelity, utilizing a limited number of patterns. LGSPI achieves superior spatial fidelity and reconstruction efficiency even at sampling ratios as low as 3%, without the need for complex post-processing or auxiliary computational frameworks. Its straightforward configuration and adaptability also make it compatible with a wide range of SPI applications, from optical encryption to hyperspectral imaging.

Principles and methods based on LGSPI

The LG function of order m and n is given by

$$v_{mn}(r, \varphi) = C_{mn} \left(\sqrt{2} \frac{r}{\omega_{0s}} \right)^{|m|} L_n^{|m|} \left(2 \frac{r^2}{\omega_{0s}^2} \right) \exp \left(-\frac{r^2}{\omega_{0s}^2} + im\varphi \right), \quad (1)$$

where is defined on polar coordinates of r and φ , $L_n^m(\xi)$ is associated Laguerre polynomials, $m = 0, \pm 1, \pm 2, \dots, \pm M$, $n = 0, \pm 1, \pm 2, \dots, N$, $M, N > 0$, ω_{0s} is the waist radius of the fundamental mode of the Gaussian beam. C_{mn} is normalization factor, and it is equal to

$$C_{mn} = \frac{1}{\sqrt{\iint |v_{mn}(r, \varphi)|^2 dr d\varphi}}. \quad (2)$$

A single v_{mn} can generate two distinct patterns, representing the real and imaginary parts, respectively. Subsequently, two sets of patterns can be derived from the segmentation of positive and negative distributions within LG functions to adapt the digital micromirror devices. Additionally, the patterns are resized and standardized to ensure compatibility with SPI reconstruction (see Supplementary Information Section 1).

The sequence of patterns observed in LGSPI imaging is contingent upon the ordering of m, n . It is established that the low-frequency information of low-order patterns has a greater weight value in the image than the high-frequency information of high-order patterns. The image is reconstructed using LG patterns with different sampling ratios, and reconstruction quality of the image is evaluated using metrics such as peak signal-to-noise ratio (PSNR) and structural similarity (SSIM).

To evaluate the quality of LGSPI, a typical image set was reconstructed at varying sampling ratios, with the imaging resolution set to 128 pixel $\times$ 128 pixel. The sampling ratio is defined as the proportion of the number of illumination patterns utilized to the total number of pixels in the target image. The imaging efficacy of LGSPI is illustrated in Fig. 1.

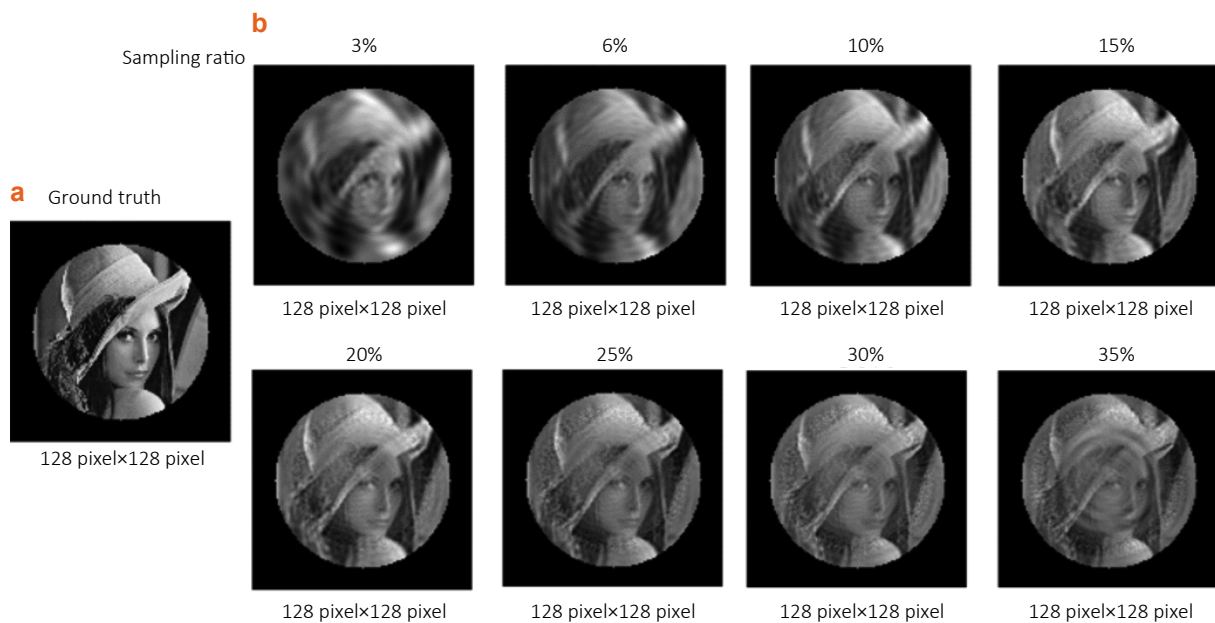


Fig. 1 | (a,b) The reconstructed results of LG method at different sampling ratios.

The typical Lena image is selected as the ground truth, as shown in Fig. 1(a). Reconstructed images under varying sampling ratios are presented in Fig. 1(b). At a sampling ratio of 3%, edge regions of the image appear blurred. As the sampling ratio increases, edge details gradually recover, and the overall image becomes sharper. At the sampling ratio of approximate 10%, the image achieves favorable clarity and detail restoration. When the sampling ratio further increases to 20%, the image exhibits richer detail, reduced noise, and a visually sharper overall appearance. The quality about reconstruction image degrades with the increase of the sampling ratio exceeding 20%. Notably, at the sampling ratio of 35%, the central region of the image becomes blurred.

Furthermore, to evaluate the noise robustness of LGSI in real-world applicability, Fig. 2 presents the reconstruction quality of the lena image under different signal-to-noise ratios (SNRs). It is seen that the SSIMs become lower with the decreasing the SNR from 20 dB to 6 dB for three different basis encodings LGSI, HIS and FSI. The SSIMs for these three bases are around 0.790, 0.760 and 0.755, respectively. And the SSIMs for HIS and FSI trend to accord at last, as the SNR decreases to 6 dB. Specially, SSIM for basis encoding LGSI is always higher than that for the other two bases. Noise analysis with varying SNR levels further strengthens the claim of real-world applicability and enhance the LGSI's robustness evaluation.

To ensure statistical validity, Table 1 presents the average reconstruction performance for 15 randomly selected images from different datasets (SPOTS-10, CTSDb and STL-10) across varying sampling ratios, where $\overline{\text{PSNR}}$ and $\overline{\text{SSIM}}$ denote the mean values of PSNR as well as SSIM. The average PSNRs initially improve with increasing sampling ratio, peaking around 10%, beyond which a grad-

ual decline is observed. Differently, SSIMs continue to rise up to a sampling ratio of 20%, reaching a maximum of 0.861, whereafter declining slightly. This degradation is attributed to the accumulation of characteristic noise from higher-order LG patterns. To meet the limited entrance pupil, the high order Laguerre-Gaussian basis is scaled, not ideal infinite. The introduced scaling factor α_{mn} is roughly set to $\alpha \propto \sqrt{(m+n)}$ (see Supplementary Information Section 1).

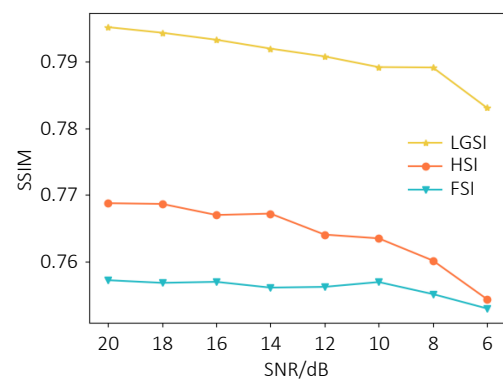


Fig. 2 | Reconstruction performance under different SNRs with different basis encodings.

The scaling Laguerre-Gaussian bases can not constitute a complete orthogonal. The mathematic deduction about high reconstruction quality with the increase of sampling ratio is not tenable. As the order increases, the discrete LG basis functions, limited by the factorial term in their polynomial expression, become less accurate, particularly at the image periphery where their intensity becomes radially concentrated. This results in reduced reconstruction fidelity at higher sampling ratios.

Table 1 | Average PSNR & SSIM evaluations for LGSI

Sample ratio	PSNR (dB)	SSIM
3%	19.140	0.770
6%	21.163	0.837
10%	21.325	0.855
15%	20.616	0.852
20%	21.056	0.861
25%	20.962	0.858
30%	20.935	0.849
35%	19.573	0.793

The number of LG patterns is jointly determined by the two parameters (M , N), allowing for a multitude of potential values at a given sampling ratio. For instance, setting (M , N) to (20, 20) yields the same sampling ratio as configurations such as (40, 10), (80, 5), and so forth. It is therefore necessary to consider the impact of different values of (M , N) on the image reconstruction results of LGSI to identify optimal parameter combinations for specific sampling ratios.

The impact of varying N on imaging performance when M is fixed at 20, 30, 40 is shown in Fig. 3(a). Similarly, Fig. 3(b) demonstrates the influence of varying M on imaging quality when N is fixed at 20, 25, 30, 35, 40. The trend lines in these figures reveal that the SSIM values are optimized for M and N . The SSIM values for N exhibit a more pronounced decline compared to the M values after reaching the peak. These results highlight the critical role of parameter selection in achieving optimal image reconstruction fidelity in LGSI systems.

To evaluate the LGSI imaging capabilities, image reconstruction of the resolution test target was performed at a low sampling ratio of 3%, as illustrated Fig. 4(a). While unsharp artifacts are evident in peripheral region of the LGSI reconstruction, their impact is significantly diminished in the central region. This phenomenon is attributed to the reduced low-order LG patterns, which result in a reduced number of features along the outer rim of the patterns.

The superiority of LGSI over HSI and FSI at very low sampling ratios is demonstrated in Fig. 4(b), where a portion of the target image is enlarged for a clarity. Experimental results further corroborate this superiority (see Supplementary Information Section 3). It's evident that only LGSI reconstruction exhibits a high degree of fidelity in this region of the image, enabling the clear discernment of the three stripes. This advantage is also supported by additional results in supplement information Section 2.

To provide a more accurately comparison of image fidelity, the pixel values of the three reconstruction results are further compared by plotting against the horizontal coordinates of the reference image, as shown in Fig. 4(c). It can be seen that only the LGSI method correctly shows the characteristics of the reference curve. In contrast and the

pixel values of the HSI and FSI do not match the reference characteristics. The curve of HSI shows erroneous peaks and the curve of FSI has only a smooth peak, further underscoring the superior performance of LGSI in preserving image fidelity at low sampling ratios.

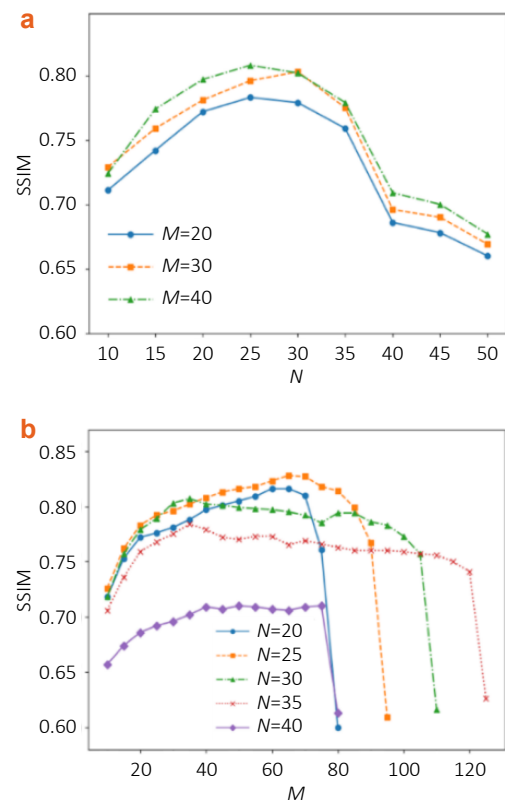


Fig. 3 | (a) The SSIM values for the LG pattern are the for different orders when $M = 20, 30, 40$. (b) different orders when $N = 20, 25, 30, 35, 40$.

To further investigate the efficiency of each pattern basis, the weight values for HSI, FSI, and LGSI, were calculated as the inner product values between the target recovery image and the patterns, as shown in Fig. 4(d-i)–(d-iii). These weights were normalized to a standard distribution with zero mean and unit variance to facilitate direct comparison. In both Hadamard and Fourier domains, significant energy concentration is observed in the early patterns of the sequence, reflecting their reliance on low-frequency components typical of natural image. On the other hand, the LGSI weight distribution is markedly more uniform across the pattern sequence, indicating that LGSI effectively exploits a broader range of spatial frequencies, including high-order LG patterns, thereby enhancing image reconstruction capability even under extremely sparse sampling conditions.

Compared to the Fourier pattern, which rely on a single trigonometric angular frequency for encoding, LG patterns incorporate two degrees of freedom for coding: angular and radial component. Mathematically, the coefficient of the trigonometric function in the LGSI method transitions from a constant (as in FSI) to a function, introducing

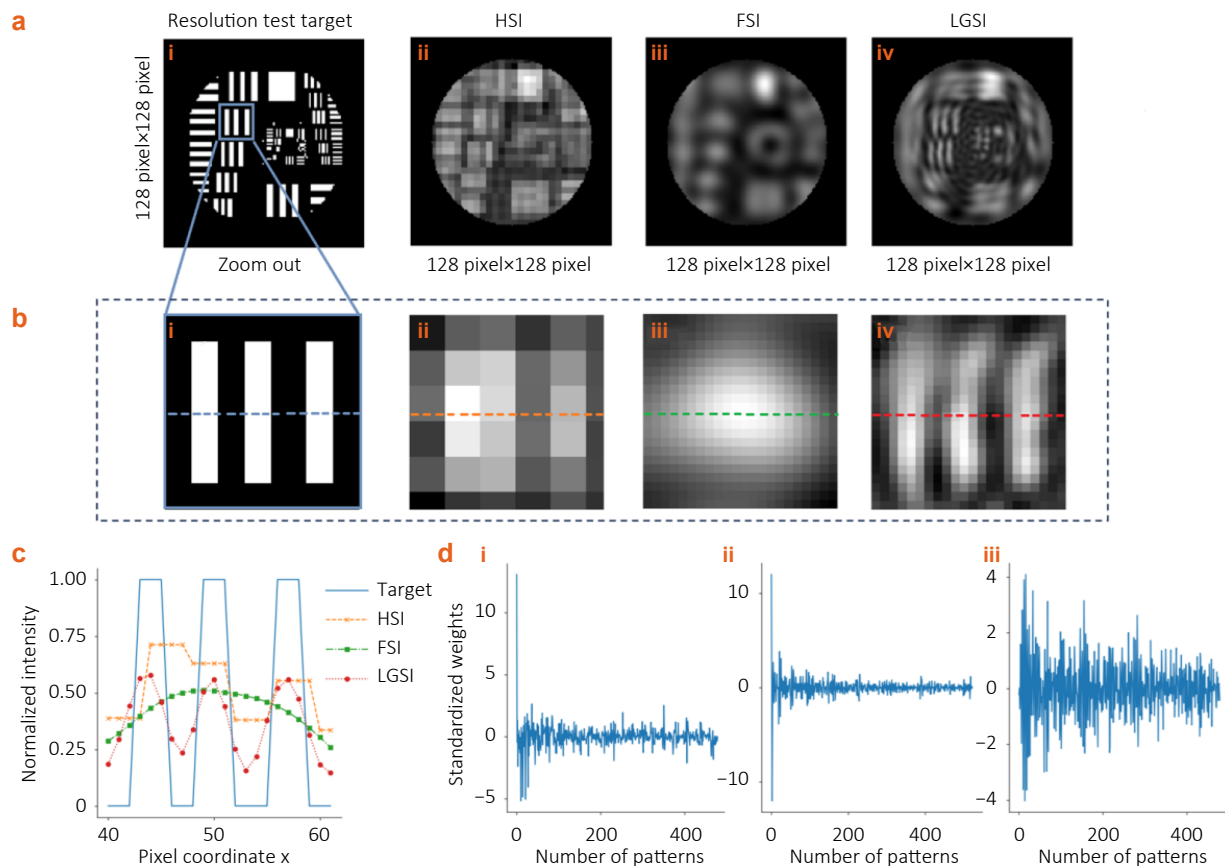


Fig. 4 | (a-i) Ground truth. (a-ii)–(a-iv) The reconstructed results with HSI, FSI and LGSI using 480 patterns. (b-i) Local enlarge areas of (a-i). (b-ii)–(b-iv) Local enlarge areas of image in (a-ii)–(a-iv). (c) Standardized intensities of corresponding line profiles in (a). The weights of Hadamard (d-i), Fourier (d-ii) and LG (d-iii) patterns in resolution test target.

greater flexibility and dimensionality in pattern coding. This increased dimensionality in the base pattern coding of LGSI highlights its superiority and indicates that the LG patterns possess stronger feature representation. The results demonstrate that LGSI achieves more uniform weight distributions and superior image reconstruction fidelity, particularly at low sampling ratios, validating its enhanced feature representation and coding efficiency.

Results and discussions

To experimentally validate the efficacy of the proposed SPI system, an optical experimental setup was established (see Supplementary Information Section 3). The experimental system employed transmissive sheet patterns of NCU logo and USAF resolution test chart as target objects. The illumination modulation pattern was set to a pixel resolution of 128×128 . To demonstrate the effectiveness of LGSI imaging at low sampling ratios, a sequence of LG patterns was generated for object illumination. The reconstructed results are shown in Fig. 5. The reconstruction capacity of LGSI was benchmarked with that of HSI and FSI with the results shown in Fig. 6, highlighting the superior imaging fidelity and efficiency of LGSI, particularly under low sampling conditions.

As demonstrated in Fig. 5, the achieved reconstructions using LGSI maintain robust imaging capacity even at reduced sampling ratios. With increasing sampling ratios, the clarity of the reconstructed images improves, as showed in Fig. 5(a)–(b). At sampling ratios 15% and 20%, more pronounced fluctuations are observed, indicating enhanced contrast in the reconstruction results. However, the characteristic features of the LG patterns become discernible and induce background noise, as can be seen in Fig. 5(c). Figure 5(d) displays the normalized intensity curves of the corresponding line scan profiles in Fig. 5(c). The curve exhibits minimal fluctuation with insignificant variations at the sampling ratio of 3%. As the sampling ratio increases, the curve's fluctuations gradually intensify, particularly at the sampling ratio of 20% where three distinct peaks emerge. This evolution indicates that within a certain range, increasing the sampling ratio progressively enhances the reconstruction resolution, improves detail clarity, and amplifies contrast, thereby enabling more accurate representation of feature information within the image.

Figure 6(a-i)–(a-iii) highlights the superior image clarity of LGSI compared to HSI and FSI, particularly at lower sampling ratios. The discernible contour in Fig. 6(a-iii) stands in stark contrast to the indistinct contours observed

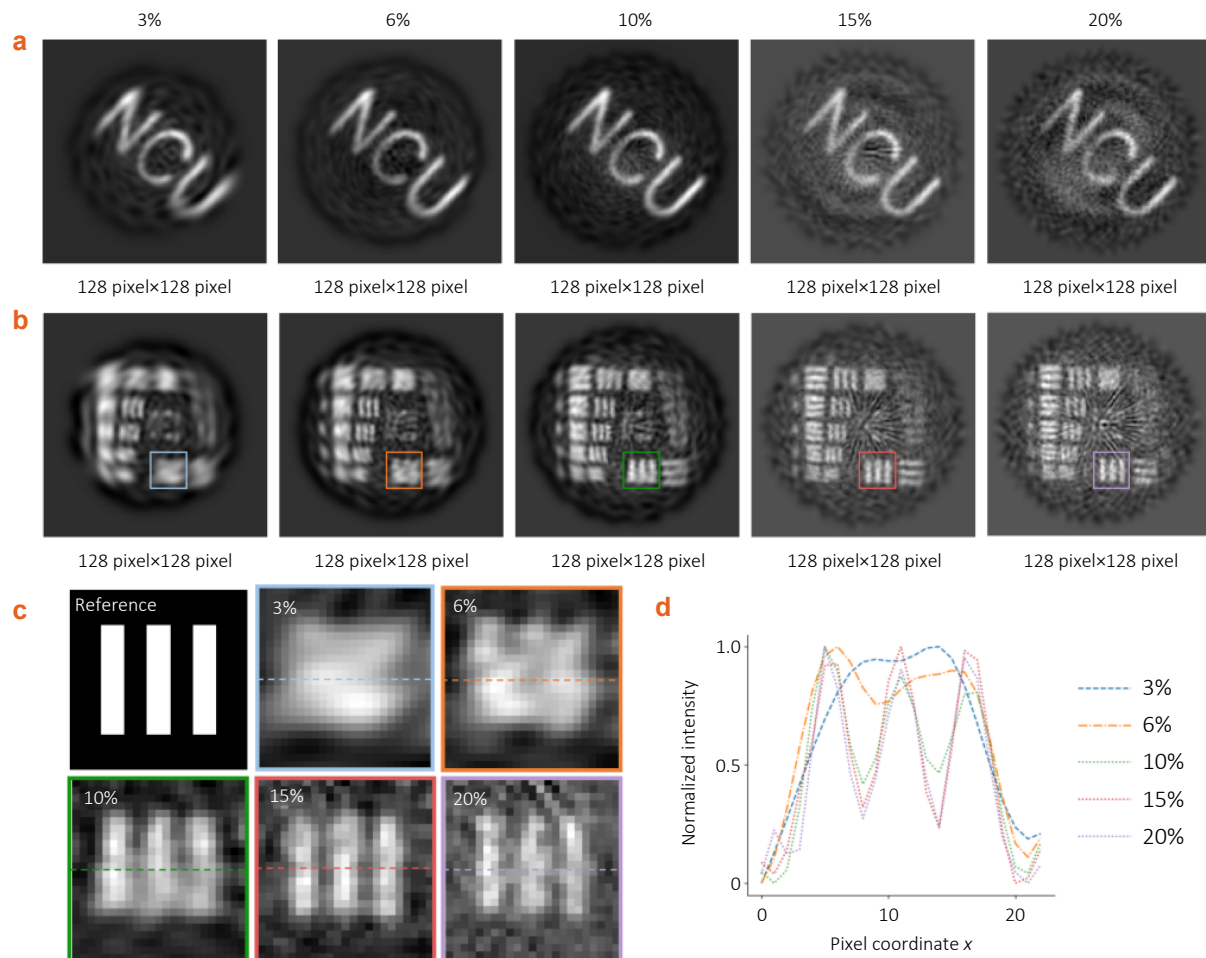


Fig. 5 | Experimental reconstructed images of (a) NCU and (b) USAF resolution test chart at different sampling ratios with LGSI method. (c) Comparison of local enlarge imaging areas enclosed in (b). (d) Normalized intensities of corresponding line profiles in (c).

in Fig. 6(a-i) and Fig. 6(a-ii). As demonstrated in Fig. 6(c-i)–(c-iii), at the same measurement levels, LGSI consistently delivers more accurate reconstruction outcomes. Notably, LGSI eliminates the mosaic effect commonly associated with HSI and effectively suppresses artefactual noise in the imaging area compared to FSI.

The Fourier transformed images corresponding to Fig. 6(c-i)–(c-iii) are shown in Fig. 6(d-i)–(d-iii), respectively, while Fig. 6(e) displays the normalized power spectrum curves. Figure 6(f-i) displays the original image of the target object, while Fig. 6(f-ii) presents its corresponding Fourier spectrum. The results demonstrate significant differences among these three methods. The curve for LGSI exhibits the closest resemblance to the reference curve, indicating its superior capability in preserving spectral information. In contrast, the curve for FSI shows intensity values approaching zero in the high-frequency region, signifying the loss of high-frequency information. This observation validates FSI's characteristic of utilizing only low-frequency information during undersampling image reconstruction. These results reveal distinct differences among the methods, with the LGSI curve being closest to the reference. It is

particularly evident that FSI reconstructs images at low frequencies, thereby confirming the limited presence of high-frequency information, as evidenced by Fourier spectrograms and power spectrum curves.

Conclusions

We have proposed and experimentally validated a physically enhanced high-fidelity and low-sampling-ratio SPI technique by utilizing the orthogonal mechanism of physical LG moments. Unlike conventional HSI and FSI, where imaging performances is highly sensitive to sampling strategies and optimization algorithms, our LGSI provides a facile and optimization-free approach to developing novel and high-performance imaging toolkit. LGSI achieves exceptional image fidelity with an extremely low sampling ratio (3%), yielding $\overline{\text{SSIM}}$ of 0.770 and $\overline{\text{PSNR}}$ of 19.140 dB. Both the experimental and simulation results demonstrate excellent agreement, further validating the robustness of the proposed method.

To substantiate the imaging capability of LGSI method, the calculated power spectra were compared with those of HSI and FSI under identical low sampling condition. The

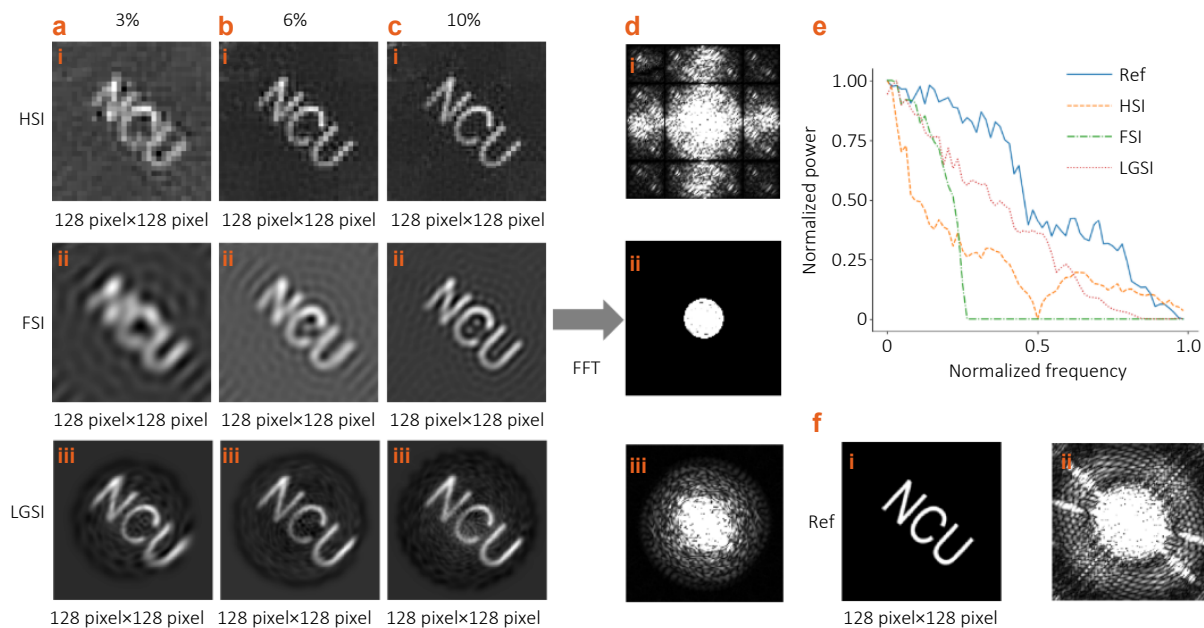


Fig. 6 | Reconstructions of NCU with HSI, FSI and LGSI. (a-i)-(c-iii) Reconstructions at different sampling ratios with three methods. (d-i)-(d-iii) The Fourier spectrum images corresponding of (c-i)-(c-iii). (e) Normalized power spectrum curves of (d-i)-(d-iii). (f-i) Original image of object and (f-ii) the corresponding Fourier spectrum.

results confirm the superiority of LGSI in capture high-frequency information and achieving higher fidelity in image reconstruction. The spatially structured modulation enabled by physical LG moments holds potential for applications in complex amplitude SPI, diffraction free high-fidelity imaging of complicated scenes, and multi-dimensional light manipulation integrated with other advanced optical techniques.

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Author contributions

Junyi Xiong: writing – original draft, visualization, validation, investigation. Can Su: data acquisition/analysis/interpretation, methodology. Zhiyuan Wang: methodology, investigation, formal analysis. Yangyang Xiong: validation, software, methodology. Hongjie Wang: methodology, investigation. Mengqiang Cai: writing – review & editing, supervision, investigation, Funding acquisition. Guiyuan Cao: sample fabrication, discussing. Zhongquan Nie: Writing – review & editing, supervision. Weichao Yan: writing – review & editing, writing – original draft, supervision, project administration, funding acquisition, conceptualization. Baohua Jia: writing – review & editing, supervision.

Competing interests

The authors declare no competing financial interests.

Supplementary information

Supplementary information for this paper is available at <https://doi.org/10.67704/ioe.2025.250003>



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