

**COMPUTATIONAL CAMERA WITH AN EXTENDED
FIELD OF VIEW: DEMONSTRATION OF A NOVEL
SYSTEM CONCEPT WITH INFORMATION EFFICIENT
DESIGN**

RITIKA MALIK



**DEPARTMENT OF PHYSICS
INDIAN INSTITUTE OF TECHNOLOGY DELHI
JULY 2025**

© Indian Institute of Technology Delhi (IITD), New Delhi, 2025

COMPUTATIONAL CAMERA WITH AN EXTENDED FIELD OF VIEW:
DEMONSTRATION OF A NOVEL SYSTEM CONCEPT WITH INFORMATION
EFFICIENT DESIGN

by
Ritika Malik

*A dissertation Submitted in fulfillment of the
requirements of the degree of*
Doctor of Philosophy



– Department of Physics –
Indian Institute of Technology, Delhi
New Delhi, India 110016

July, 2025

To my parents, teachers, & siblings

For your endless support,
unwavering belief, and constant encouragement.

I dedicate this work to you with all my gratitude.

THESIS CERTIFICATE

This is to certify that the thesis entitled, "**Computational Camera with an Extended Field of View: Demonstration of a Novel System Concept with Information-Efficient Design**," submitted by **Ms. Ritika Malik** to the Indian Institute of Technology Delhi, in partial fulfillment of the requirements for the award of the degree of **Doctor of Philosophy**, is a bonafide record of original research work conducted under our supervision.

To the best of our knowledge, the work presented in this thesis meets the requisite academic standards. **Ms. Ritika Malik** has fulfilled all the necessary requirements for the submission of her thesis, and this research has not been submitted in part or full to any other institution or university for the award of any degree or diploma.

Prof. Kedar B. Khare

Thesis Supervisor

Department of Physics &
Optics and Photonics Center (OPC)

Indian Institute of Technology Delhi

New Delhi, India - 110016

Prof. Ravikrishnan Elangovan

Thesis Co-Supervisor

Department of Biochemical Engineering
and Biotechnology

Indian Institute of Technology Delhi

New Delhi, India - 110016

New Delhi, July 2025

If I have seen further, it is by standing on the shoulders of giants

— Isaac Newton,

"Letter to Robert Hooke: 1675"

ACKNOWLEDGMENTS

I am deeply grateful to everyone who has contributed in one way or another to shaping my journey throughout this research. Their insights, encouragement, and support have been invaluable in bringing this work to fruition.

This thesis represents my effort to explore computational imaging systems from an information transfer perspective, focusing on how optical design influences information capture and how computational techniques can enhance this capability. While not every avenue explored led to concrete results—whether due to unforeseen challenges in simulations or the need for deeper investigation—each step has been a learning experience. The progress documented here is the result of numerous stimulating discussions, particularly with my advisor, Prof. Kedar Khare, whose guidance, insightful discussions, and unwavering encouragement have been pivotal in the completion of this work.

I also wish to acknowledge the esteemed faculty members, including Prof. P. Senthil Kumar, Prof. P.K. Gupta, and Prof. Kedar Khare, whose expertise and mentorship in optics have significantly enriched my knowledge and research capabilities. I also appreciate Prof. Apurna Mehara for her foundational lessons in optimization and multivariate statistics.

My early PhD days were enriched by my collaboration with Dr. Sarita Ahlwat at PhaseLab startup, where I explored DHM-related projects. I am also indebted to my co-supervisor, Prof. Ravikrishnan, for introducing me to single molecular imaging. Despite the challenges faced, this experience broadened my understanding and skills across different disciplines, contributing significantly to my development as a researcher.

I would like to express my sincere gratitude to the University Grant Commission (UGC) for funding my research during the initial phase of my PhD and providing me the flexibility to explore various projects until I identified experiments of significant interest. I also thank PMRF for supporting my participation in conferences, symposiums, and further research activities, which have been instrumental in advancing my work. I am deeply grateful to the PMRF review committee for their rigorous annual evaluations and critical feedback, which have helped refine my research projects for the better. Additionally, I acknowledge the High-Performance Computing (HPC) facilities at IIT Delhi for providing essential computational resources that have helped me in accelerating my simulation studies.

Finally, I am deeply grateful to my family and friends for their constant support and encouragement throughout this journey. A special thanks to my mother Mrs. Saroj Devi and my sister Ms. Anamika Malik for their constant emotional support and belief in me—I couldn't have done it without them.

ABSTRACT

Computational imaging is a methodology that comprises the joint design of optical hardware and inverse algorithms to indirectly collect and retrieve an object's information from the recorded data, even if the data is not immediately interpretable. By leveraging this approach, we have engineered a novel imaging system that achieves an extended field of view while retaining near-diffraction-limited resolution, thereby enhancing the system's overall information capacity. This enhancement is achieved by strategically exploiting the inherent signal structure of the object through sophisticated encoding techniques embedded within the optical system design.

In this dissertation, I will provide a comprehensive explanation of my research on "*extended field of view imaging*." The objective is to enhance the space bandwidth product or information capacity of the computational imaging system by making modifications to the optical hardware through point spread function engineering and computational recovery algorithms. We show theoretically and experimentally an increment in field of view by a factor of 2 over the conventional imaging system. Our technology enables a system to capture a single-shot image with increased field of view (FoV) performance without compromising the native image resolution. We have also demonstrated the analogous relation between our study and structured illumination microscopy (SIM), which expands the Fourier domain rather than the spatial domain.

These findings guide us towards generalizing the concept of information capacity for computational imaging systems, a topic that will be explored in detail later in this dissertation. I describe this approach as "*information-efficient design*" since it facilitates encoding information tailored to specific experimental requirements. Additionally, we have examined the impact of detector bit depth on the design of computational imaging systems. This investigation led to the proposal of a new data-domain information measure that leverages the characteristics of detected information to predict system performance a priori to image reconstruction.

This work aims to establish a comprehensive framework for analyzing computational imaging systems, devise algorithms to solve related inverse problems, and determine the practical limits on recoverable information using a computational imaging system. Compressive imaging, which involves acquiring a small number of measurements, plays a critical role in this work. It efficiently reconstructs images with sparse object information and addresses challenges caused by the discrete, quantized nature of the measurements.

कम्प्यूटेशनल इमेजिंग एक ऐसी पद्धति है जिसमें ऑप्टिकल हार्डवेयर और व्युत्क्रम एल्गोरिदम का संयुक्त डिज़ाइन शामिल है ताकि रिकॉर्ड किए गए डेटा से किसी वस्तु की जानकारी को अप्रत्यक्ष रूप से एकत्र किया जा सके और फिर एल्गोरिदम के माध्यम से उस जानकारी को पुनर्प्राप्त किया जा सके, भले ही रिकॉर्डेड डेटा तुरंत समझने योग्य न हो। इस दृष्टिकोण का लाभ उठाते हुए, हमने एक नया इमेजिंग सिस्टम विकसित किया है जो विवर्तन-सीमित (near-diffraction-limited) रिज़ॉल्यूशन को बनाए रखते हुए एक विस्तारित दृश्य क्षेत्र (field of view) प्राप्त करता है, जिससे सिस्टम की समग्र सूचना क्षमता में वृद्धि होती है। यह वृद्धि ऑप्टिकल सिस्टम डिज़ाइन में अंतर्निहित परिष्कृत एन्कोडिंग तकनीकों के माध्यम से वस्तु की अंतर्निहित सिग्नल संरचना का रणनीतिक रूप से लाभ उठाकर हासिल की जाती है।

इस शोध प्रबंध (dissertation) में, मैं "विस्तारित दृश्य क्षेत्र इमेजिंग" पर आधारित अपने शोध का विस्तृत विवरण प्रस्तुत करूँगी। इसका उद्देश्य पॉइंट स्प्रेड फंक्शन इंजीनियरिंग और कम्प्यूटेशनल रिकवरी एल्गोरिदम के माध्यम से ऑप्टिकल हार्डवेयर में संशोधन कर कम्प्यूटेशनल इमेजिंग सिस्टम की स्पेस-बैंडविड्थ प्रोडक्ट अथवा सूचना क्षमता को बढ़ाना है। हमने सैद्धांतिक और प्रयोगात्मक रूप से यह दर्शाया है कि पारंपरिक इमेजिंग प्रणालियों की तुलना में हमारे सिस्टम में दृश्य क्षेत्र (field of view) में लगभग 2 गुना की वृद्धि होती है। हमारी तकनीक एक सिंगल-शॉट प्रणाली है, जो मूल छवि रिज़ॉल्यूशन से समझौता किए बिना विस्तारित दृश्य क्षेत्र को एक ही इमेज में कैप्चर करने में सक्षम बनाती है। इसके अतिरिक्त, हमने अपने अध्ययन और स्ट्रक्चर्ड इल्यूमिनेशन माइक्रोस्कोपी (SIM) के बीच एक समानता भी प्रदर्शित की है, जो स्थानिक डोमेन (spatial domain) के बजाय फूरियर डोमेन का विस्तार करता है।

ये निष्कर्ष हमें कम्प्यूटेशनल इमेजिंग सिस्टम के लिए सूचना क्षमता की अवधारणा को सामान्यीकृत करने की दिशा में मार्गदर्शन करते हैं। यह विषय इस शोध प्रबंध में आगे विस्तार से विवेचित किया जाएगा। मैं इस दृष्टिकोण को "सूचना-कुशल डिज़ाइन" के रूप में वर्णित करती हूँ, क्योंकि यह विशिष्ट प्रायोगिक आवश्यकताओं के अनुरूप सूचना को एन्कोड करने की सुविधा प्रदान करता है। इसके अतिरिक्त, हमने कम्प्यूटेशनल इमेजिंग सिस्टम के डिज़ाइन पर डिटैक्टर बिट डेप्थ (bit-depth) के प्रभाव का अध्ययन किया है। इस विश्लेषण के परिणामस्वरूप, हमने एक नया डेटा-डोमेन सूचना मापदंड प्रस्तावित किया है, जो प्राप्त सूचना की विशेषताओं का उपयोग करके इमेज पुनर्निर्माण से पहले ही सिस्टम के प्रदर्शन का पूर्वानुमान लगाने में सक्षम है।

इस शोध का उद्देश्य कम्प्यूटेशनल इमेजिंग प्रणालियों के विश्लेषण के लिए एक समग्र ढांचा स्थापित करना, संबंधित इनवर्स समस्याओं को हल करने हेतु एल्गोरिदम विकसित करना, तथा कम्प्यूटेशनल इमेजिंग सिस्टम के माध्यम से पुनः प्राप्त की जा सकने वाली सूचना की व्यावहारिक सीमाओं का निर्धारण करना है। इस कार्य में कम्प्रेसिव इमेजिंग की एक महत्वपूर्ण भूमिका है, जिसमें सीमित मापनों के माध्यम से डेटा अधिग्रहण किया जाता है। यह पद्धति विरल वस्तु सूचना वाले चित्रों का कुशलतापूर्वक पुनर्निर्माण करती है और मापन की विसंलग्न (discrete) तथा क्वांटाइज्ड प्रकृति से उत्पन्न चुनौतियों का समाधान करती है।

CONTENTS

CERTIFICATE	i
ACKNOWLEDGMENTS	ii
ABSTRACT	iv
List of Figures	x
List of Tables	xxii
List of Listings	xxiii
List of Acronyms	xxiv
1 Thesis	
1 Introduction and Roadmap	1
1.1 Overview	1
1.2 Main Contributions	5
1.3 Thesis Structure	7
2 Unconventional Imaging: A PSF Engineering Perspective and Information Metrics	10
2.1 Introduction	10
2.1.1 Computational Imaging	11
2.1.2 Imaging and Field of View	13
2.2 Linear Shift Invariant Imaging System	17
2.2.1 Image Formation in an imaging system	18
2.3 Point Spread Function Engineering	23
2.3.1 Extended Depth of Field	24
2.3.2 Depth Encoding	28
2.3.3 Extended FoV	32
2.4 Output in the form of basis expansion	34
2.5 Information Capacity of an Imaging System	36
2.5.1 Information Capture via Compressive Sampling	38
2.6 Summary	42
3 Computational Imaging With Extended FoV	44

3.1	Introduction to Extended FoV	44
3.2	Related work	44
3.3	Extended FoV: Principles and Insights	47
3.4	A Mathematical Perspective	49
3.4.1	Sampling requirement of Phase Mask	51
3.5	Extended FoV as a Spatial Analog to SIM	54
3.6	Simulation Result	60
3.6.1	Reconstruction of Binary Object	61
3.6.2	Reconstruction of Grayscale Object	62
3.6.3	Impact of Object Sparsity on Extended FoV Reconstruction	64
3.6.4	Impact of noise on Extended FoV reconstruction	66
3.7	Pictorial Analysis of Information Capacity With MPIR	67
3.8	Summary	70
4	Image reconstruction algorithm	71
4.1	Introduction	71
4.2	Inverse Problem Formulation Using Basis Representation	71
4.2.1	Forward Model in Basis Representation	72
4.2.2	Inverse Problem Formulation	75
4.3	Conditioning of imaging system matrix	78
4.3.1	Even Distribution of Signal Energy	78
4.3.2	Condition Number and Randomness	79
4.3.3	Sparsity and Incoherence:	81
4.3.4	Theoretical Guarantees:	83
4.4	Algorithms for Recovering Extended FoV Object Information	84
4.4.1	Optimization Framework for Signal Reconstruction	85
4.4.2	Algorithm 1: Alternating Minimization via Gradient Descent	86
4.4.3	Algorithm 2: Alternating Minimization via Proximal Gradient Descent	90
4.5	Summary	94
5	Experimental Demonstration of extended FOV	95
5.1	Imaging System components	95

5.1.1	Köhler illumination	95
5.1.2	Spatial Light Modulator	97
5.1.3	Phase Mask generation using CGH	99
5.1.4	Experimental Validation of Phase Mask	101
5.2	Practical Challenges in Implementing Extended FoV with MPIR	103
5.2.1	Calibration and Image Reconstruction	103
5.3	Simulation Study for Optimal PSF design	108
5.3.1	Necessary Conditions	109
5.3.2	Sufficient condition	115
5.4	Experimental Demonstration	116
5.4.1	Experimental Results	117
5.5	Summary	119
6	A new information measure for computational imaging	121
6.1	Introduction	121
6.2	Information Capacity of an imaging system	122
6.2.1	Information Capacity in Low-SNR Conditions	123
6.2.2	Information Capacity in high SNR condition	125
6.3	A Data Domain Information Measure	125
6.3.1	Implications of the Information Measure	129
6.4	Summary	132
7	Conclusion and Future direction	134
7.1	Summary of Thesis Work	134
7.2	Extensions and Future directions	136
7.3	Conclusion	138
	Bibliography	139
II	Appendix	
A	Appendix:	
	Mathematical Framework for Image Formation	160
A.1	Basis Representation of an Object Signal	160

A.1.1	Duality Between Sampling and Fourier Basis	161
A.2	Eigenfunction analysis of Imaging system	166
B	Appendix :	
	Algorithmic Implementation of Extended FoV	171
B.1	Total Variation Regularization	171
B.1.1	Matlab implementation of TV	172
B.2	MATLAB Implementation of Algorithm 1: Alternating Minimization via Gradient Descent	174
B.2.1	Main Script	174
B.3	MATLAB Implementation of Algorithm 2: Alternating Minimization via Proximal Gradient Descent	180
B.4	MATLAB Implementation for Condition Number Analysis of MPIR	183
B.4.1	Main Script: mpir_psf_svd_visualization.m	183
B.4.2	Helper Function: conv_svd.m	184
C	Appendix:	
	MATLAB Implementation of Calibration Techniques	186
C.1	MATLAB Implementation of CGH using GS-algorithm	186
C.1.1	Main Script	186
C.2	Matlab Implementation of PSF estimation technique.	187
	Publications	192
	Biographical Sketch	195

LIST OF FIGURES

Figure 1.1	Components of a computational imaging system. The system consists of three fundamental components: (1) an encoding hardware, which modulates object information as it propagates through the optical system; (2) a digital sensing device, which detects, samples, and quantizes the optical signal; and (3) a computational algorithm, which processes the detected data to reconstruct and extract the object information. . . .	1
Figure 2.1	Schematic representation of a traditional imaging system, where high-quality optics bear the sole responsibility for image formation. Inspired by the human eye model, the system features a lens at the front and a sensor at the back. The recorded image closely approximates the original object information, with post-processing applied only for visual enhancement.	11
Figure 2.2	Conceptual representation of a computational imaging system, emphasizing the integration of front-end optics and post-processing algorithms. The technique that was first used in the seminal work of Cathey <i>et al.</i> [55]. In this approach, object information is encoded through the modification of optical components to produce an intermediate image that differs from the original object. The post-processing unit subsequently reconstructs the original object information from the encoded data.	12
Figure 2.3	Schematic of a typical microscopy setup, highlighting the key optical components and the relationship between magnification and FoV. The FoV is primarily defined by the diameter of the eyepiece’s field stop diaphragm.	14
Figure 2.4	Conceptual representation of a typical photographic camera setup, illustrating the key optical components and the relationship between sensor size, focal length, and the angular field of view (θ). The ray diagram demonstrates how light converges through the lens to form an image on the sensor, with θ representing the angular extent of the captured FoV.	15

Figure 2.5	The optical architecture of a canonical $4F$ system , illustrating the key components: an input plane for object placement, two lenses separated by their focal lengths (f), and an intermediate Fourier plane where spatial frequency information is processed. This setup serves as a fundamental model for linear, shift-invariant (LSI) imaging systems, enabling analysis and modification of imaging properties.	18
Figure 2.6	Comparison of PSFs at different depths for conventional and computational imaging systems employing cubic phase and log-asphere phase mask designs. The top row corresponds to the conventional imaging system, with (a) showing the aperture having a constant phase. The middle row corresponds to an imaging system with a cubic phase mask (e) generated using a phase modulation parameter $\alpha = 5 \times 10^{-5}$. The bottom row presents the log-asphere lens (i), featuring a radially increasing phase function. While the PSF of the conventional system (panels b–d) degrades significantly with increasing defocus, the cubic phase (panels f–h) and log-asphere (panels j–k) designs yield PSFs that remain nearly invariant across depth. This will induce a uniform blur across different depth planes, thereby facilitating a straightforward deconvolution to enable an effective reconstruction of extended depth information.	26
Figure 2.7	Illustration of a log-spherics lens designed for variable focal length across its aperture. The lens surface is segmented into concentric annular rings, each engineered to focus light from a specific axial distance $s(r)$ defined as a function of the ring radius. The focal length decreases from the center toward the periphery, which enables the lens to maintain focus over a broad depth range. This design results in an extended depth of field by combining focused contributions from different annular regions, with each correspond to distinct object depths.	27

Figure 2.8	Pictorial representation of depth-encoding PSFs at different axial positions. Shown are PSFs from a conventional imaging system (top row), rotating PSF (RPSF) (second row), double-helix PSF (DH-PSF) (third row), and Tetrapod PSF (bottom row). The conventional PSF rapidly deteriorates with defocus and loses its structural coherence. In contrast, the RPSF exhibits continuous rotation of its pattern with axial displacement, the DH-PSF displays two distinct lobes that rotate predictably with the depth, and the Tetrapod PSF shows four well-defined lobes whose geometry evolves smoothly across the axial range. These engineered PSFs encode depth information into their spatial structures to enable a precise three-dimensional localization from two-dimensional measurements.	31
Figure 2.9	Pictorial representation of extended FoV PSF. (a) The single point impulse response (SPIR) represents the diffraction-limited PSF of a conventional imaging system. It is shown as a single Gaussian impulse with local blur simulated using a 5×5 pixel Gaussian kernel. (b) The MPIR consists of multiple Gaussian impulses distributed across the sensor's active region and illustrates the engineered PSF used for multiplexing the extended FoV information. (c) The phase mask generated by the standard Gerchberg–Saxton (GS) algorithm is designed to produce the MPIR pattern at the system's Fourier plane.	33
Figure 2.10	Illustration of the image acquisition process in a traditional imaging system. The object information is digitized at the Nyquist rate by projecting it onto a sampling basis ϕ . A total of N discrete measurements are captured and then processed computationally to enhance the information content of the final image.	39
Figure 2.11	Illustration of the image acquisition process in a computational imaging system. The object information is digitized at a sub-Nyquist rate by integrating sampling and compression. Compression is achieved by first projecting the object signal onto an appropriate basis ϕ , followed by sampling using the basis ψ . A total of $M < N$ discrete measurements are captured, requiring an inverse algorithm for computational reconstruction of the object information.	40

Figure 3.1	Resolution vs. FoV: (a) A conventional imaging system captures a high-resolution image with a limited FoV. (b) Increasing the FoV results in a loss of resolution, causing image blur. (c) Objective: Expanding the FoV while maintaining resolution, where the dotted circle represents the original FoV and the larger circle illustrates the extended FoV. . . .	45
Figure 3.2	Pictorial Representation of the Extended FoV Principle. (a) Complete object information within the full FoV. (b) Single point impulse response (SPIR) approximated as a delta impulse at the center of the field. (c) Limited FoV recorded by the native sensor, with the active sensor area marked by the yellow dotted square. (d) Proposed PSF with MPIR. (e) Scrambled data containing information from outside the sensor boundary, captured by the limited-size sensor. (f) Mapping of different FoV regions onto the full object FoV, corresponding to distinct impulses. (g-j) Visual representation of how object information from outside the native sensor boundary is brought into the active sensor region, corresponding to different impulses.	48
Figure 3.3	Schematic for extended FoV imaging with a phase mask at the Fourier plane. The phase mask encodes the object field, with the detector (yellow square) capturing a scrambled image. The larger (black) square represents the desired FoV.	51
Figure 3.4	Structured Illumination Microscopy: Expanding Fourier Space for Enhanced Resolution In conventional microscopy, the resolution is fundamentally limited by the numerical aperture (NA) of the imaging system, which restricts the highest spatial frequencies that can be captured. This restriction is represented as a circular region in Fourier space (red circle). SIM enhances the resolution by employing a structured illumination pattern, typically sinusoidal, which introduces three shifted frequency components in Fourier space (red dots). The structured illumination interacts with the sample and shifts the high-frequency information into the system's native frequency range (blue circle) through the convolution between object's spectrum and the Fourier transform of the illumination pattern. By acquiring a series of images with different phase shifts and orientation, SIM effectively extends the Fourier space coverage (dotted circle) to computationally reconstruct isotropically high-resolution image.	55

Figure 3.5	Extended FoV imaging: Expanding Spatial Domain Beyond Sensor Limits In conventional imaging, the sensor's physical dimensions constrain the maximum FoV which restricts the amount of spatial information that can be captured. This limitation is represented by the native sensor boundary, shown as the red square or the dotted yellow circle in the image. The extended FoV methodology overcomes this limitation by using a MPIR as the system's PSF which introduces multiple impulses at distinct spatial locations (red dots). When convolved with the object function, MPIR generates multiple spatially shifted replicas of the object. These shifted copies redistribute object details originally beyond the sensor's boundaries into the detector's active region (blue square) which effectively encodes additional spatial information. By capturing a single scrambled measurement containing these multiplexed images, the extended FoV system employs computational reconstruction to recover a wider FoV while preserving the system's native resolution. . . .	58
Figure 3.6	Reconstruction of Extended FoV with binary image. (a),(b) Reconstructed images from the scramble data in Fig. 3.2(e). (a) Recovered image using PSF with delta impulses, (b) Recovered image using PSF with Gaussian impulses. In both cases the information beyond the native sensor size, i.e. the letters "P" and "E" get recovered completely. (c) Relative mean square error (RMSE) as a function of iteration numbers with solid blue line and dotted red line representing the error (on log-scale) when PSF with delta impulses and Gaussian impulses is used respectively.	61

Figure 3.7	Simulation results demonstrating extended FoV reconstruction for a grayscale object. (a) Ground truth image of size 256×256 pixels. (b) Image captured with a native sensor of size 128×128 pixels (dotted yellow square) and a detector size of 150×150 pixels (dotted white square), where information outside these sensor regions is lost in a conventional measurement process. (c) Captured data using the proposed PSF, with yellow and white dotted squares indicating the respective sensor sizes. (d), (i) Reconstructed images for the 128×128 sensor using a PSF with delta and Gaussian impulses, respectively. (e), (j) Reconstructed images for the 150×150 sensor using a PSF with delta and Gaussian impulses, respectively. (f) PSF with Gaussian impulses, with a zoomed-in view of an individual impulse shown in (g). (k) Relative mean square error (MSE) plots for both sensor sizes: solid blue and red curves represent results for the 128×128 and 150×150 sensors, respectively, with delta impulses as the PSF. The corresponding MSE plots for Gaussian impulses are shown by the dotted lines	63
Figure 3.8	Cameraman Image with Increasing Levels of Sparsity: (a)-(c) Ground truth images processed with median filters of sizes 3×3, 7×7, and 13×13, corresponding to Tamura coefficient (TC) values of 1.46, 1.61, and 1.7, respectively. (d)-(f) Reconstructed images after 1000 iterations. The MPIR extent and sensor size are confined within the central 128×128 pixel window for all cases.	65
Figure 3.9	RMSE Performance of Restored Images: RMSE values after 1000 iterations plotted as a function of object sparsity, quantified using the Tamura coefficient (TC). The blue dot corresponds to the blurred cameraman image simulated with increasing sparsity levels, as illustrated in Fig. 3.8. The upper and lower red dots represent the cameraman image and the binary "PHASE" object, respectively; both are reconstructed using the MPIR PSF without median filter smoothing.	66
Figure 3.10	RMSE Performance of Restored Images: RMSE variation as a function of different signal-to-noise ratio (SNR) levels (in dB).	67

Figure 3.11	MTF comparison of an imaging system with and without MPIR The MTF of a conventional imaging system affected by spherical aberration (blue curve) exhibits severe lines of zeros, which leads to significant information loss and instability in inverse problem-based image reconstruction [38]. In contrast, incorporating MPIR (red curve) scatters these zeros, and producing a more uniform MTF with reduced variation. While minor fluctuations persist, they can be mitigated using appropriate regularization techniques during image reconstruction [100]. Moreover, this MTF flattening allows higher eigenmodes information to propagate through the system with minimal attenuation, thereby significantly enhancing the imaging system's overall information capacity.	69
Figure 4.1	Mathematical model of the proposed imaging system. The target object x undergoes transformation through the measurement matrix $\hat{A}$, resulting in a scrambled representation. These scrambled measurements are then captured by a limited FoV sensor, modeled by the truncation operator $\hat{S}$. The resulting vector y represents the captured data, which is spatially constrained by the sensor's finite detection area.	74
Figure 4.2	Standard approaches for regularizing linear inverse problems. An overview of commonly used techniques for stabilizing the solution of linear inverse problems. These methods include least-squares estimation for well-conditioned systems, Tikhonov regularization for addressing ill-posed problems, constrained least squares for incorporating additional constraints, and compressive sensing techniques for under-determined systems, which leverage l_0 - and l_1 -norm sparsity priors to restore object information.	77
Figure 4.3	Pictorial representation of multiplexed measurements via MPIR. Object information is encoded through a multiplexing process, where multiple spatial points contribute to a single pixel measurement. This many-to-one mapping ensures that signal energy is distributed evenly across multiple measurements.	79

Figure 4.4	Comparison of system matrix conditioning across different imaging configurations The ideal lens system, modeled with a single-point impulse response (SPIR) as its PSF, results in a well-conditioned system matrix ($\kappa(\mathcal{H}) = 1$), which enables a stable reconstruction without inversion. In contrast, the extended FoV system utilizes a multiplexed PSF (MPIR), which provides a better conditioning of the system matrix $\kappa(\mathcal{H}) = 256.13$, compared to the bare sensor system, where $\kappa(\mathcal{H}) \approx 11,000$ [153]. This positions MPIR as an intermediate solution between these two extremes. The analysis highlights the trade-off between extending the FoV and maintaining numerical stability in image reconstruction. (Further details on the plot are available in the appendix b.4)	80
Figure 5.1	Pictorial representation of an SLM. An incoherent light wavefront (from an LED or collimated source) interacts with the SLM, where the displayed grayscale phase mask modulates its phase. Each grayscale level corresponds to a specific voltage that adjusts the liquid crystal (LCs) orientation and refractive index, thereby introducing a controlled phase shift in the incident light.	98
Figure 5.2	Visual representation of an GS algorithm. A step-by-step illustration of the GS algorithm for phase retrieval. The process iterates between the spatial and Fourier domains, enforcing amplitude constraints in the spatial domain while updating the phase in the Fourier domain. This iterative refinement continues until the reconstructed intensity closely matches the target MPIR distribution, which results in the optimized phase mask for SLM encoding.	101
Figure 5.3	Experimental Validation of CGH (a) Simulated MPIR pattern with 41 impulses positioned within the central half of the computational window. (b) Corresponding phase mask generated using the GS algorithm. (c) Experimentally obtained MPIR pattern in the first-order diffraction with unmodulated zero-order.	102
Figure 5.4	Pictorial representation of PSF estimation problem. (a) Measured intensity which is obtained by blurring the reference intensity (b) using the PSF (c). The constrained minimization approach (Eq. 5.12) estimates the unknown blur function (c) by leveraging the reference and measured intensity information.	106

Figure 5.5	Spatially varying PSF estimation using Siemen star as a standard object: The figure illustrates the PSF estimation process for an image affected by spatially varying blur. The blurred image is shown in Fig. (a, d, e) alongside PSFs at different orientations in Fig. (b, e, f). The restored blur functions are presented to the right of Fig. (b, e, f). A line plot through the center of the PSFs in Fig. (b, e, f) demonstrates the fidelity of the reconstructed blur function in comparison to the original.	107
Figure 5.6	Intensity variation in experimental MPIR. (a) Experimentally recorded first-order MPIR demonstrating intensity variations among impulses. (b) Weight factors are computed for each impulse relative to its nearest neighbor, which provide quantitative insight into the intensity distribution.	108
Figure 5.7	Simulation of image reconstruction with the varying number of impulses in a PSF. Panels (a ₁)-(a ₃) display MPIR with an increasing number of impulses along the dotted yellow squares. Panels (b ₁)-(b ₃) illustrate how the spatial variation in recovered information depends on the overlap area, with the effective FoV represented by the dotted red square. As the number of impulses increases, the information content of the reconstructed image (c ₁)-(c ₃) increases, which is reflected in an increasing energy parameter (d ₁). However, the contrast parameter (d ₂) decreases which results in poorer reconstruction quality, as evident in panel (c ₃).	113
Figure 5.8	Simulation of image reconstruction with varying spatial extent of PSF. Panels (a ₁)-(a ₃) display MPIRs with PSF extents indicated by the dotted yellow squares: smaller (64×64), comparable (128×128) and larger (256×256) than the detector size of (128×128) pixels. Spatial variation in recovered information depends on the overlapped area in (b ₁)-(b ₃) with an effective FoV represented by the dotted red square. With the extent of PSF, the information content of the reconstructed image (c ₁)-(c ₃) decreased as seen in the plot of the energy parameter (d ₁) while the contrast parameter (d ₂) exhibits an increasing trend. The slight decrease in the plot of R on for small extent of impulses is due to the fact that the extended FOV is not covering the whole object.	114

Figure 5.9	Experimental setup for the extended FOV system: The sample is uniformly illuminated via Köhler illumination using a spatially incoherent 650 nm LED source. A phase mask corresponding to MPIR is generated as a CGH and projected onto the SLM to transform the system's PSF from SPIR to MPIR. The modulated light is then reflected by a beam splitter and captured by the sCMOS sensor as a scrambled image for subsequent computational processing.	117
Figure 5.10	Extended FoV results. (a1) Image recorded without MPIR coding in first order at native resolution of the system, (a2) MPIR captured using a pinhole object with 9 impulses. The dotted yellow rectangle shows the PSF extent. (a3) Scrambled data captured by a small FoV sensor is shown in the blue rectangle. (a4) Overlapped area representing the spatial variation of recovered information with the dotted red square representing the effective FOV increment. (a5) Recovered extended FoV information beyond the blue square.	118
Figure 5.11	Extended FoV results. (a1) Image recorded without MPIR coding in first order at native resolution of the system, (a2) MPIR was captured using a pinhole object with 41 impulses. The dotted yellow rectangle shows the PSF extent. (a3) Scramble data captured by a small FoV sensor is shown in the blue rectangle. (a4) Overlapped area representing the spatial variation of recovered information with the dotted red square representing the effective FoV increment. (a5) Recovered extended FoV information beyond the blue square. (a6) Profile plot through the dotted line in first-order image along with reconstruction for the resolution of the reconstructed image	119
Figure 6.1	Illustration of information capacity as a function of signal-to-noise ratio (SNR). The blue curve represents the traditional information measure (eq.6.6), which dominates at high SNR levels. The red curve corresponds to the information measure derived from the measured data, which becomes dominant in low SNR conditions. This demonstrates that in low-SNR scenarios, each pixel measurement has a greater impact on the system's overall information capacity compared to high-SNR conditions.	124

Figure 6.2	Impact of detector bit-depth on recorded bandwidth. (a) The standard cameraman test image is first zero-padded and blurred using a 5×5 Gaussian impulse response kernel. (b-d) The blurred image is then digitized using sensors with 2-bit, 4-bit, and 16-bit quantization. As bit-depth increases (e-g), energy in the Fourier domain becomes more compact, which illustrates the relationship between quantization levels and effective bandwidth. Here, the effective bandwidth is defined as the relative area in Fourier space that contains 99% of the total energy in the raw data after bit quantization.	127
Figure 6.3	Empirical relationship between the bandwidth of detected raw data and bit depth. The plot shows the normalized bandwidth of the recorded images as a function of quantization bit depth. Each data point represents the mean bandwidth computed across all test images, while the shaded region indicates the standard deviation, which captures data variability.	128
Figure 6.4	Siemens star reconstructions under different J_D parameters or with different bit-depth and measurement conditions: (a) Ground truth (b) MPIR as PSF. (c) Measured data (d) reconstruction with 16-bit with full measurements, (e) reconstruction with 4-bit with full measurements, (f) reconstruction with 10-bit with one-third of measurements, and (g) reconstruction with 4-bit with one-third of measurements. Zoom-in images (h-k) represent the reconstruction of high-frequency components.	130
Figure 6.5	Reconstruction with similar J_D values: (a) A binary test object ("Optics") with lower complexity. (b) Scrambled measurement data with $4\times$ fewer samples. (c) Reconstructed object. (d) A grayscale test object ("Cameraman") with higher complexity. (e) Scrambled measurement data with $2\times$ fewer samples. (f) Reconstructed object. Despite differences in object complexity, by adjusting the number of pixel measurements to achieve comparable J_D values, a similar reconstruction performance can be attained.	132
Figure a.1	Eigenfunction behavior in an LSI system: Illustration of how an eigenfunction of a linear shift-invariant (LSI) system retains its functional form after passing through the system and is scaled by its corresponding eigenvalue.	168

Figure a.2 **Conceptual illustration of image formation using eigenfunction expansions in an LSI system.** (a) The object function is decomposed into the system's eigenbasis, with each coefficient determined by projecting the object signal onto the corresponding eigenfunction. (b) As these basis components pass through the LSI system, they are scaled by their respective eigenvalues. The final output image is then formed by the weighted sum of these scaled basis functions. 170

LIST OF TABLES

Table 3.1	Table for error performance of reconstructed images for different sparsity levels: The table compares the reconstruction errors for a binary text image and a grayscale cameraman image, each characterized by different degrees of sparsity. Sparsity is measured using the Tamura Coefficient (TC) of the gradient magnitude image. It highlights the relationship between image structure and reconstruction accuracy.	64
Table 5.1	Table for reconstruction error analysis for varying impulse parameters in MPIR. The table compares image reconstruction quality under two scenarios: (i) varying the number of impulses while keeping the extent (128×128 pixels) fixed and (ii) varying the spatial extent while maintaining a fixed number (29) of impulses. Reconstruction performance is evaluated using RMSE, PSNR, and SSIM, which demonstrates the impact of these parameters on reconstruction accuracy.	115
Table 6.1	Table for the error performance corresponding to different J_D values. The table presents the reconstruction error metrics, including relative root mean square error (RMSE) and peak signal-to-noise ratio (PSNR), for various J_D values.	131

LISTINGS

b.1	Total variation functional and gradient	172
b.2	Data Generation with MPIR PSF	174
b.3	Main iterative reconstruction loop	175
b.4	Huber TV penalty and gradient computation	178
b.5	FFT-based 2D convolution	179
b.6	FFT-based 2D correlation (adjoint convolution)	179
b.7	Main iterations with Proximal Gradient Descent	180
b.8	Condition number estimation using SVD of a circulant matrix formed from the MPIR-PSF	183
b.9	Function to compute SVD of circulant matrix from 1D PSF	184
c.1	GS-Based Phase Mask Generation for MPIR Intensity Distribution	186
c.2	PSF Estimation with Gradient Descent and Huber Regularization	188
c.3	Function to generate Binary Siemen Star object	190

ACRONYMS

CCD	Charge-Coupled Device
CMOS	Complementary Metal-Oxide-Semiconductor
FOV	Field of View
DOF	Depth of Field
SBP	Space-Bandwidth Product
PSF	Point Spread Function
LSF	Line Spread Function
ISO	International Organization for Standardization
CGH	Computer-Generated Holography
MPIR	Multiple Point Impulse Response
SLM	Spatial Light Modulator