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Differentiable Imaging: Progress, Challenges, and Outlook

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Differentiable imaging has emerged as a transformative paradigm in computational imaging by enabling end-to-end optimization of integrated optical-computational systems. This review examines how differentiable frameworks bridge the persistent gap between physical reality and computational models, effectively addressing fundamental challenges in uncertainty quantification, system design, and computational complexity. We analyze recent advances demonstrating how this approach simultaneously optimizes physical and computational elements while enhancing reconstruction accuracy beyond traditional limits. The framework's capacity to systematically address both deterministic uncertainties, such as manufacturing tolerances and alignment errors, and stochastic uncertainties, including sensor noise and environmental fluctuations, has enabled unprecedented robustness in real-world imaging applications. We identify emerging challenges in numerical modeling, computational efficiency, and system integration, with particular focus on how digital twin architectures may provide solutions for next-generation adaptive imaging systems. Looking forward, we discuss critical opportunities in theoretical foundations, system innovation, and scientific applications, highlighting how differentiable imaging is poised to not only revolutionize imaging technology itself but also accelerate scientific discovery through artificial intelligence-enabled, physics-consistent computational methods.

Introduction

Imaging technology has fundamentally transformed our ability to observe and understand the world across scales. From nanoscale cellular structures to distant astrophysical phenomena, modern imaging systems serve as critical windows into domains beyond natural human perception [1]. These technological advances have revolutionized scientific exploration, enabling researchers to visualize and analyze phenomena with unprecedented resolution, sensitivity, and dimensionality.

The evolution of imaging technology has shifted dramatically from purely optical systems toward sophisticated computational-optical platforms. This transition represents more than incremental improvement—it marks a fundamental reconceptualization of the imaging process itself. By integrating advanced algorithms with optical hardware, modern systems transcend traditional limitations, achieving remarkable capabilities in resolution enhancement [2–4], multi-dimensional imaging, and dynamic range expansion, while simultaneously reducing system complexity and cost [5,6].

Computational imaging stands at the center of this transformation, leveraging sophisticated algorithms that work in concert with optical hardware to form and reconstruct images. This approach has enabled groundbreaking applications including super-resolution microscopy, quantitative phase imaging, and 3-dimensional reconstruction [2,3]. A distinguishing feature of modern computational imaging is its emphasis on co-design—the simultaneous optimization of physical and computational components as an integrated system rather than separate entities [1,7]. The impact of these innovations extends beyond research laboratories into diverse sectors including medical diagnostics, industrial quality control, public safety, and defense systems.

Despite these advances, practical implementation of computational imaging systems faces 2 fundamental challenges. The first arises from physical–numerical model mismatch, where real-world systems deviate from theoretical models in complex and often unpredictable ways [8]. This mismatch stems from multiple sources of uncertainty that cascade through the imaging pipeline: deterministic factors introduce systematic errors through manufacturing tolerances and optical aberrations [9]; mechanical misalignments alter intended light paths [10,11]; and stochastic uncertainties manifest through environmental fluctuations and fundamental measurement limitations [12]. These accumulated uncertainties degrade reconstruction quality and undermine system reliability.

The second challenge involves managing the escalating computational complexity inherent in advanced imaging modalities. Techniques such as hyperspectral imaging [13] and time-resolved measurements [14] generate massive, high-dimensional datasets that exceed conventional processing capabilities. Standard image processing operations—denoising, deconvolution, and feature extraction—become exponentially more demanding when applied to these complex datasets. System-specific algorithms must further accommodate unique characteristics including optical aberrations and environmental conditions [15,16], creating substantial computational bottlenecks, particularly for real-time applications.

Differentiable imaging emerges as a groundbreaking paradigm that addresses these fundamental challenges by seamlessly integrating physical system modeling with computational optimization [17–22]. This approach systematically manages uncertainty by incorporating explicit numerical models for deterministic variations while harnessing differentiable optimization frameworks to handle stochastic fluctuations. At its core, differentiable imaging embeds physically accurate models within sophisticated learning architectures, enabling true end-to-end system optimization while preserving crucial physical interpretability.

This review synthesizes recent advances in differentiable imaging and explores how this paradigm transforms computational imaging systems at multiple levels. We begin by examining the theoretical foundations of differentiable imaging, establishing how it fundamentally reconceptualizes the relationship between physical and computational components. We then analyze recent progress across 3 key dimensions: addressing physical–numerical model mismatches through uncertainty quantification; enabling sophisticated system co-design through end-to-end optimization; and extending imaging capabilities while compensating for hardware limitations. Through careful examination of current challenges and emerging research directions, we provide insights into the trajectory of next-generation imaging technologies, revealing how differentiable imaging not only addresses present limitations but also opens new possibilities for future imaging systems that combine physical accuracy with computational efficiency.

Differentiable Optical Imaging

At its foundation, a computational imaging system operates through the interplay of 2 fundamental processes: physical encoding and computational decoding. Understanding this interplay, as illustrated in Fig. 1, reveals both the remarkable potential and inherent limitations of current imaging approaches.

The encoding stage represents the physical journey of electromagnetic waves from an object to our final measurement. This process begins as light interacts with our object of interest, travels through an intricate optical system, and ultimately reaches electronic sensors. The physics involved carries substantial complexity—light sources illuminate the scene with specific characteristics; optical elements shape the light's path through reflection, refraction, and diffraction; and electronic sensors transform incoming photons into measurable

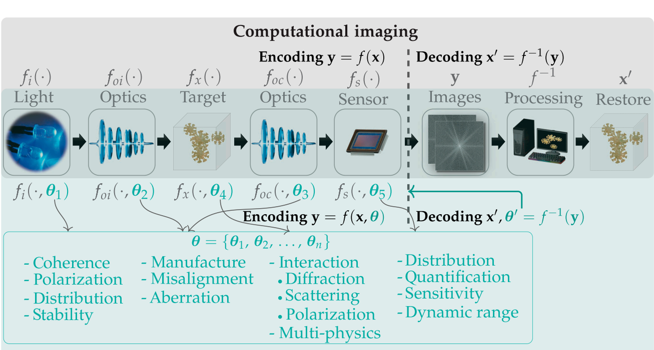

Fig. 1. Overview of computational imaging and differentiable imaging.

signals. We can express this sophisticated process mathematically as $\mathbf{y} = f(\mathbf{x})$, where $\mathbf{x}$ is the light radiation that represents the object's properties as a vector, $f(\cdot)$ encompasses the entire system transformation, and $\mathbf{y}$ represents our measurements.

The decoding stage then faces the challenge of reconstructing desired physical quantities of the light radiation from these measurements [2]. This reconstruction process moves beyond traditional digital image processing by incorporating the underlying physics of the imaging system. Rather than treating images as pure data structures, the decoding algorithms must account for how light physically interacted with our system, requiring precise understanding of the encoding process. While this physics-aware approach enables more accurate reconstructions, it also introduces considerable computational complexity.

In practice, computational imaging faces a fundamental challenge in bridging theoretical models with physical reality. Modern imaging systems comprise numerous interacting components, each introducing its own uncertainties and complexities. Light sources exhibit temporal fluctuations, optical elements contain manufacturing imperfections, sensors introduce various forms of noise, and environmental variations continuously alter system performance parameters. Current approaches typically diverge into 2 extremes: they either oversimplify these physical systems through idealized mathematical models, sacrificing accuracy for tractability, or rely heavily on deep learning techniques that achieve high performance but sacrifice physical interpretability.

The conventional practice of separating encoding and decoding processes creates substantial challenges in computational imaging. This artificial division between physical hardware and computational algorithms—components that should function as a unified system—leads to accumulated discrepancies between theoretical models and actual system behavior. When hardware optimization follows metrics disconnected from computational requirements, or when algorithms make unrealistic assumptions about physical systems, overall performance inevitably suffers.

As defined in Ref. [19]:

Differentiable imaging is a computational imaging paradigm where certain aspects of the problem are parameterized as differentiable, irrespective of whether the inverse problems are tackled by numerical optimization, neural networks, or a combination of the two.

By leveraging differentiable programming and automatic differentiation (AD), differentiable imaging offers an elegant solution to the limitations of conventional computational imaging. Rather than pursuing increasingly complex yet cumbersome physical models, differentiable imaging fundamentally reconceptualizes the imaging process [19,23,24]. It transforms the traditional encoding model $\mathbf{y} = f(\mathbf{x})$ into a more comprehensive formulation $\mathbf{y} = f(\mathbf{x}, \boldsymbol{\theta})$, where $\boldsymbol{\theta}$ represents a parameter set specifically designed to address and compensate for mismatches between physical systems and numerical models. The complete forward model captures the entire imaging pipeline through a series of interconnected transformations:

$$\mathbf{y} = f(\mathbf{x}, \boldsymbol{\theta}), \qquad f = f_{noise} \circ f_c \circ f_{oc} \circ f_x \circ f_{oi} \circ f_i, \tag{1}$$

where the function composition operator $\circ$ connects each system component, and $\boldsymbol{\theta} = \{\boldsymbol{\theta}_c, \boldsymbol{\theta}_{oc}, \ldots\}$ encompasses all system parameters. Each component corresponds to specific physical processes within the imaging system, from illumination characteristics through object interactions to sensor behavior and noise sources.

This comprehensive forward model enables the formulation of an elegant inverse problem that simultaneously optimizes system parameters while reconstructing images:

$$\mathbf{x}^*,\ \ \theta^* = \arg\ \min_{\mathbf{x},\theta}\mathcal{L}\left(f\left(\mathbf{x},\theta\right),\mathbf{y}\right) + \sum_{n=1}^{N}\beta_n\mathcal{R}_n(\mathbf{x}) \qquad \text{s.t.} \quad \mathbf{x}\in\Omega_{\mathbf{x}},\ \ \theta\in\Omega_{\theta} \tag{2}$$

Here, $\mathcal{L}\left(f(\mathbf{x},\theta),\ \mathbf{y}\right)$represents the fidelity term that quantifies the discrepancy between the model predictions and measured data. While the ℓ_2 loss $\mathcal{L}\left(f(\mathbf{x},\theta),\ \mathbf{y}\right) = \left|f(\mathbf{x},\theta),\ \mathbf{y}\right|^2$is commonly used due to its mathematical tractability, and compatibility with Gaussian noise assumptions, the selection of an appropriate fidelity function depends critically on the specific imaging conditions and noise characteristics. For imaging scenarios dominated by Poisson noise (common in low-photon-count regimes like fluorescence microscopy), negative log-likelihood or Kullback-Leibler divergence-based losses often prove more effective. In cases with outliers or heavy-tailed noise distributions, robust loss functions such as Huber loss or ℓ_1 norm can provide superior performance. Specialized applications may benefit from composite or perceptual loss functions that incorporate domain-specific knowledge. The regularization terms $\mathcal{R}_n(\cdot)$ weighted by factors β_n impose prior knowledge about the solution space, while the physical constraints $\Omega_{\mathbf{x}}$ and Ω_{θ} ensure that solutions remain within realistic physical bounds [19].

While AD provides computational convenience, the fundamental value of differentiable imaging lies in its problem-driven approach that directly addresses the critical mismatch between theoretical models and real-world optical systems. This approach enables genuine end-to-end optimization where optical configurations and reconstruction algorithms are jointly optimized within a unified framework. The capacity to address model-reality misalignment has historically been the primary obstacle to achieving true system-algorithm co-design in computational imaging. Differentiable imaging overcomes this challenge by creating a cohesive optimization strategy that simultaneously addresses multiple sources of uncertainty and system imperfections within a single framework. While manual gradient calculation might theoretically yield comparable results in simple cases, this approach becomes impractical for complex imaging systems with numerous interdependent parameters. In systems where variables interact in non-linear ways, manual gradient calculation becomes prohibitively challenging or impossible. Differentiable programming overcomes these limitations by calculating gradients for entire algorithmic processes rather than isolated mathematical expressions, enabling application to problems that resist straightforward mathematical formulation. Computational imaging inherently spans multiple disciplines—optical design, fabrication, and inverse problem solving—with potential mismatches emerging at each stage. Differentiable imaging provides a coherent framework that bridges these disciplinary gaps and optimizes the entire imaging pipeline holistically. The integration of physically accurate models with efficient optimization techniques allows imaging systems to adapt to real-world conditions while maintaining theoretical rigor, creating a powerful new paradigm for advancing imaging science and technology.

Progress of Differentiable Optical Imaging

The evolution of differentiable imaging has fundamentally transformed computational imaging by enabling unprecedented integration between physical systems and computational models. As illustrated in Fig. 2, this transformation spans 3 key dimensions: first, addressing physical–numerical model mismatches through comprehensive uncertainty quantification; second, enabling sophisticated system co-design through end-to-end optimization; and third, extending imaging capabilities while compensating for hardware limitations. These advances have not only enhanced system efficiency but have also pushed imaging capabilities beyond traditional limits. The following sections examine each of these developments in detail.

Bridging the numerical–physical model mismatch

As illustrated in Fig. 1, optical system uncertainties arise from multiple interacting sources that create mismatches between physical reality and numerical models. These uncertainties span deterministic factors like optical aberrations and system misalignment, stochastic elements including sensor noise and environmental variations, and epistemic uncertainties stemming from incomplete system understanding. Differentiable imaging has emerged as a powerful framework for addressing some of these challenges.

Addressing deterministic uncertainties

The precise mathematical description of physical components represents a fundamental challenge in imaging system design. Even minor deviations from ideal behavior—whether from manufacturing tolerances, alignment errors, or inherent system limitations—can substantially impact imaging performance. These challenges manifest differently across imaging modalities, each requiring specific consideration.

In holographic imaging, for instance, the reconstruction quality depends critically on precise knowledge of the object-to-sensor distance, as phase information proves particularly sensitive to spatial relationships [25,26]. Similarly, pixel super-resolution lensless imaging must contend with mechanical scanning uncertainties that can arise from light source, sample, or sensor movements [27,28]. Multiple-plane phase retrieval faces its own alignment challenges during translation scanning [29].

These challenges become particularly acute in systems requiring multiple measurements. Ptychography demands precise alignment between illumination and sample, with reconstruction quality heavily dependent on positioning accuracy [11]. Fourier ptychography microscopy (FPM) faces additional complexities from light-emitting diode (LED) array imperfections in translation, rotation, and manufacturing position [30–32]. Beyond these alignment issues, optical element imperfections themselves can introduce substantial imaging artifacts [9,33–36].

Traditional approaches to addressing these alignment and calibration challenges relied heavily on sequential corrections: auto-focusing algorithms in holography [25,26], digital alignment in ptychography [9], and image registration in pixel super-resolution lensless imaging [37]. However, these sequential methods often fall short because they artificially segment the forward model into discrete steps, ignoring the intricate interplay between different components of the encoding process. This separation inevitably leads to error accumulation that compromises final imaging performance.

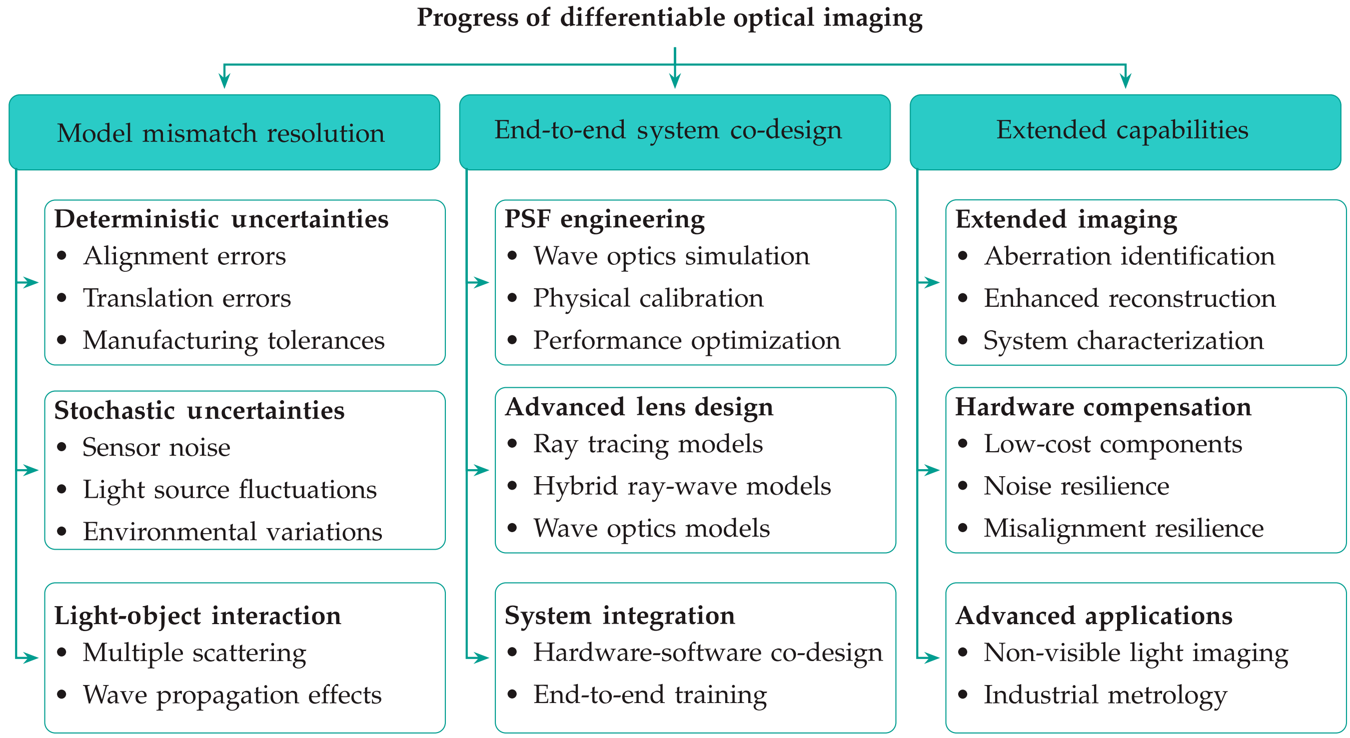

Fig. 2. Progress of differentiable imaging.

Differentiable imaging transforms this approach by enabling simultaneous optimization of all modelable uncertainties. This unified strategy delivers 2 crucial advantages: it ensures a more accurate forward model in the inverse imaging process while eliminating the cumulative errors inherent to sequential processing. Recent applications demonstrate the power of this approach across various imaging modalities.

In holographic imaging, differentiable imaging enables concurrent autofocusing and complex field reconstruction [38], achieving single-shot complex field imaging from one inline hologram. For pixel super-resolution lensless imaging, the framework simultaneously optimizes scanning positions, sample-to-sensor distance, and complex field reconstruction [39], delivering superior results compared to sequential methods. Multiple-plane phase retrieval benefits from the optimization of individual plane locations [40] or affine transformations between measurement planes [41] alongside complex field reconstruction.

The benefits extend particularly to advanced imaging techniques like ptychography and Fourier ptychography. In conventional ptychography, differentiable imaging enables simultaneous probe and object estimation [42,43], offering improved speed, accuracy, and robustness through flexible error metrics and prior information [44–47]. For Fourier ptychographic microscopy (FPM), the framework allows correction of LED array misalignment and optical element aberrations simultaneously with complex field reconstruction [48], pushing system performance beyond traditional limits.

Recent advances have further expanded these capabilities. A new differentiable framework for imaging system calibration using implicit neural networks and splines enables gradient-based optimization of uncertain measurement coordinates [20]. This approach improves reconstruction quality in miscalibrated systems like computed tomography by properly accounting for coordinate uncertainty. Similarly, in exoplanet imaging, differentiable rendering frameworks now leverage wavefront sensing data to refine aberration estimates and improve starlight subtraction, achieving substantial enhancements in contrast and detection limits without requiring additional reference images [49].

Dealing with stochastic uncertainties

Stochastic uncertainties [50] present a distinct set of challenges throughout the imaging pipeline. Unlike deterministic uncertainties that can be modeled precisely, stochastic effects manifest through unpredictable variations: light sources fluctuate temporally, sensors introduce random noise and cross-talk effects, and environmental conditions change unpredictably. These combined effects degrade measurement quality and introduce artifacts that traditional imaging approaches struggle to address.

FPM provides an illuminating example of these challenges in practice. Darkfield measurements, which capture crucial high-frequency information about the sample, typically suffer from poor signal-to-noise ratios. Traditional approaches attempted to address this limitation through hardware solutions, such as increasing exposure times or implementing high dynamic range processing [12,51]. Additionally, vignetting effects compromise illumination uniformity across the field of view, leading to measurement distortions that substantially impact reconstruction quality [52,53]. Recent advances suggest a more sophisticated approach to managing these uncertainties. By reconsidering how we process captured information, researchers have discovered that dark-field images can be understood as bandpass-filtered representations of the sample, where edge features dominate the signal. This insight has enabled novel processing approaches in the feature domain that prove more robust to noise and artifacts [54–56]. Differentiable imaging enhances system optimization through precise modeling and inverse optimization. This framework enables the development of sophisticated objective functions that explicitly address stochastic system variations [48]. By incorporating these mathematical advances, FPM systems can achieve high-quality imaging with reduced hardware requirements, overcoming traditional limitations in measurement time and sensor specifications. As demonstrated in Fig. 3, the advantages of this approach become particularly evident when dealing with multiple practical system imperfections. Under challenging conditions, including system misalignment, optical aberrations, and limited sensor performance, uncertainty-aware Fourier ptychography (UA-FP) substantially outperforms conventional reconstruction methods. This robust performance illustrates how differentiable imaging effectively handles multiple sources of uncertainty while maintaining reconstruction quality.

Modeling complex light–object interaction

The interaction between light and matter lies at the heart of optical imaging, yet accurately modeling these interactions remains one of the field's most substantial challenges. Traditional approaches typically relied on simplified mathematical descriptions that reduce complex physics of wave propagation, scattering, and diffraction into manageable equations [57]. While these simplified models offer computational advantages, they often sacrifice physical accuracy, failing to capture the intricate interplay between light and matter that characterizes real-world imaging scenarios.

The limitations of simplified models become particularly evident in advanced imaging applications. Consider optical diffraction tomography, where light's interaction with a sample creates complex scattering patterns. The way we model this scattering process directly influences our ability to recover different sample properties [58,59]. While traditional models might capture basic scattering behavior, they often miss subtle yet important effects that could provide valuable information about the sample's structure and composition.

Differentiable imaging represents a substantial advance in our ability to model these complex interactions. By incorporating sophisticated physical models within a differentiable framework, this approach enables us to address phenomena that have long challenged conventional reconstruction methods. For example, in x-ray nanotomography, differentiable imaging has pushed beyond traditional depth of focus limitations, enabling

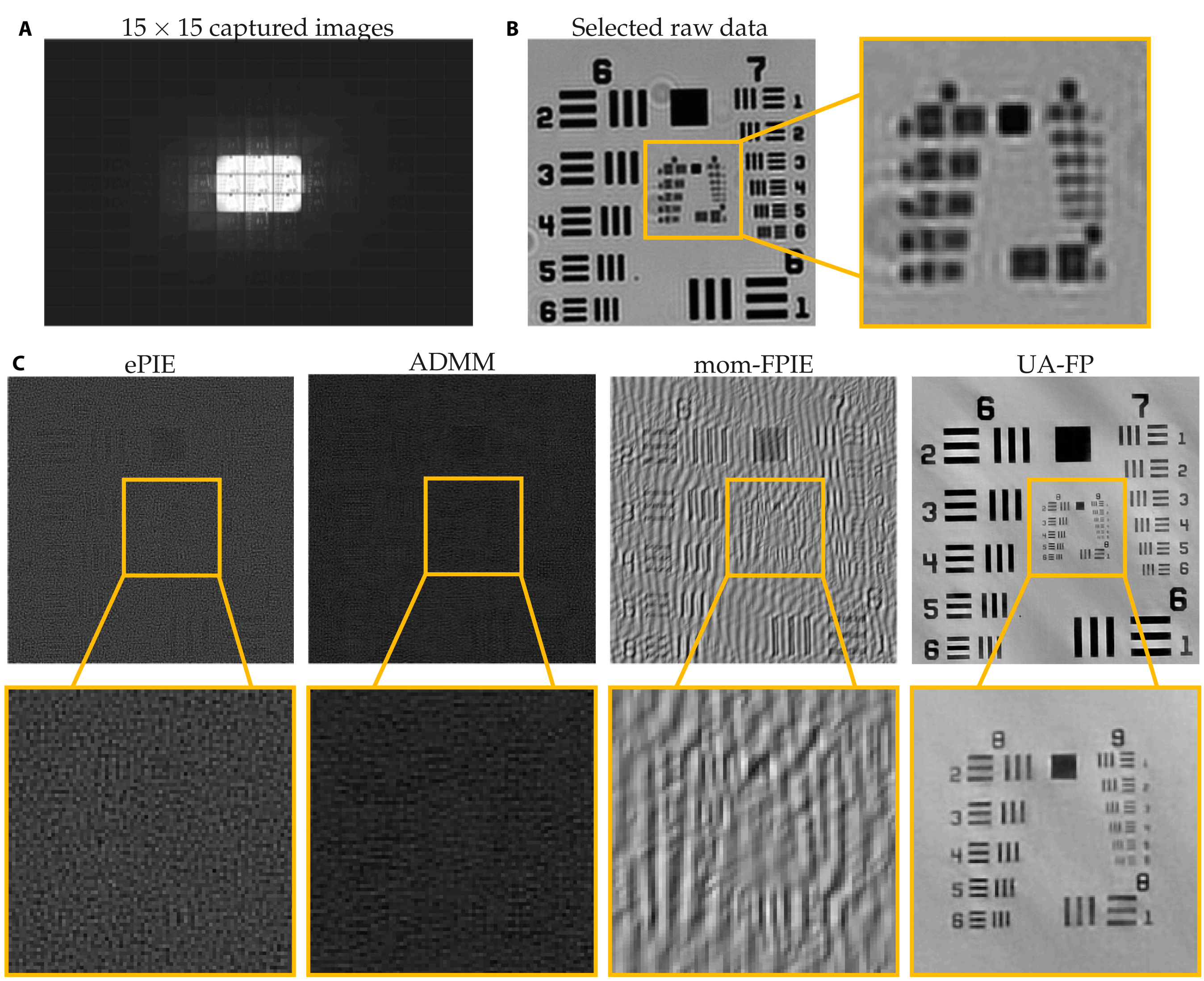

Fig 3. Uncertainty-aware Fourier ptychography (UA-FP) [48]. (A) The captured images; (B) the selected raw data; and (C) the reconstruction results of different methods.

clearer and more detailed reconstructions of nanoscale structures [60]. This breakthrough stems from the framework's ability to model and account for complex wave propagation effects that conventional approaches typically ignore. Perhaps even more striking is the application of differentiable imaging to holographic particle image velocimetry. In this field, the ability to model multiple scattering events has revolutionized high-density particle imaging [61]. Traditional holographic techniques struggle when particles become too densely packed, as multiple scattering effects begin to dominate the signal. However, by incorporating these complex scattering interactions directly into the imaging model, differentiable imaging enables accurate reconstruction even in scenarios that exceed conventional holographic limits.

End-to-end system co-design

The advent of differentiable imaging has transformed system design by enabling simultaneous optimization of optical and computational elements. This integrated approach marks a fundamental shift from traditional methods, where optical and computational components were optimized separately, often leading to suboptimal system performance. In point spread function (PSF) engineering, researchers have achieved substantial breakthroughs through co-design approaches [62–64]. A notable advancement emerged in microscope system optimization, where the challenge was reformulated as an inverse problem. By developing a differentiable wave optics simulator with trainable modules, researchers created a framework capable of simultaneous physical calibration and PSF optimization [65], demonstrating the power of end-to-end system optimization. The emergence of differentiable microscopy represents perhaps the most promising development in this direction. By incorporating trainable optical elements at strategic points along the optical path, researchers can now explore novel, interpretable microscope architectures [18]. This ability to simultaneously optimize both optical and computational elements has led to unconventional designs that substantially outperform traditional approaches, showcasing how co-design can expand the boundaries of optical system capabilities.

The integration of differentiable imaging has revolutionized lens design, transforming a process traditionally dependent on expert intuition and iterative refinement [66,67]. By incorporating gradient information into the design pipeline, researchers can now directly optimize system parameters based on performance metrics [22,68,69]. This approach fundamentally relies on representing lens optical systems as differentiable functions, enabling efficient gradient-based optimization strategies. The development of differentiable optical modeling frameworks has progressed along several complementary paths. In the domain of ray tracing, Mitsuba introduced pioneering differentiable capabilities [70,71], followed by more accessible implementations leveraging PyTorch [69]. Recent advances include hybrid ray-wave models that simultaneously account for both aberration and diffraction effects [72], enabling more comprehensive system optimization. Additionally, new differentiable Fourier optics frameworks have emerged, incorporating various optical elements, polarized light propagation, and arbitrary spatial coherence fields [73].

This mathematical foundation enables systematic exploration of design spaces, often revealing novel optical configurations that traditional methods might overlook. Recent advances have substantially expanded these capabilities across diverse applications. For complex tasks like extended source irradiance tailoring, researchers have developed sophisticated approaches using double-freeform lenses with multi-level radial basis functions [74]. The framework has proven particularly valuable for addressing practical manufacturing challenges, enabling optical degradation correction in manufacturing-perturbed glass–plastic hybrid lens systems through joint hardware–software optimization [75]. Smartphone telephoto lens design represents another substantial breakthrough [76]. A fully automated framework [77] combines optical design indicators, Delano diagrams for initialization, and comprehensive parameter optimization, including materials and high-order aspheric terms. By incorporating a differentiable PSF calculation based on the Fresnel–Kirchhoff model, this approach achieves accurate end-to-end optimization while streamlining the design process. The impact of differentiable design extends beyond traditional optics. In eye-tracking applications, researchers have developed a dense deflectometry-based method that leverages optimization-driven inverse rendering with a differentiable virtual eye model. This approach estimates eye pose and shape parameters via gradient descent, achieving improved accuracy through pixel-dense surface measurements [78]. For infrared imaging, an end-to-end framework combines differentiable ray-tracing with neural network optimization to co-design aspheric diffractive optical elements and computational restoration networks, achieving superior performance in single-lens short-wave infrared systems while enabling robust athermalization [79]. The differentiable ray-tracing engineers have also enabled algorithmic innovations, such as curriculum learning approaches that can design compound lenses from random initializations without human intervention [80].

Extended capabilities and hardware compensation

Differentiable imaging represents a fundamental advancement in computational imaging by creating a seamless bridge between physical systems and numerical models. This integration has transformed not only image quality but also the entire approach to system design and implementation, enabling capabilities that extend well beyond traditional imaging limitations.

Extending imaging and sensing capabilities

The evolution of aberration correction in imaging systems provides an illustrative example of the transformative impact of differentiable imaging. Traditional ptychographic iterative engines achieved substantial progress by enabling simultaneous reconstruction of both the sample and illumination characteristics, including the pupil function that captures system aberrations. However, these conventional approaches exhibited a fundamental limitation: while they could detect aberrations, they were unable to distinguish between those caused by misalignment and those inherent to the optical components themselves.

This inability to differentiate aberration sources created substantial challenges for system calibration and optimization [81]. In typical scenarios, an imaging system producing distorted results would be analyzed using traditional methods that might correctly identify the presence of aberrations but could not determine whether they stemmed from a misaligned lens or manufacturing imperfections in the optical components themselves [82]. This ambiguity complicated determination of appropriate corrective actions, including whether the system required realignment or component replacement. Differentiable imaging addresses this challenge through a more sophisticated approach. By incorporating detailed physical models of both optical components and potential misalignment effects into the reconstruction process, the framework can effectively separate different sources of aberration. This joint optimization of sample and illumination patterns provides not only more accurate reconstructions but also more interpretable results that can guide system maintenance and improvement. The practical implications are substantial: Fourier ptychography systems can now provide valuable data for lens metrology, enabling more precise characterization of optical components [48]. The capacity for discriminating between different aberration sources extends beyond improved image quality to enable precision metrology for optical component characterization, guided maintenance protocols based on specific degradation sources, and quantitative feedback for future optical system designs. These capabilities collectively represent a substantial advancement over traditional methods that could only identify aberration presence without determining causal factors.

Compensating for hardware limitations

The advantages of differentiable imaging become particularly evident when imaging outside the visible spectrum, where hardware limitations often impose substantial constraints. Imaging at non-visible wavelengths presents multiple challenges: optical components frequently exhibit suboptimal performance at extreme wavelengths; specialized components for ultraviolet, infrared, or x-ray imaging can be prohibitively expensive; signal-to-noise ratios typically degrade at non-visible wavelengths; precise alignment becomes increasingly challenging without visual feedback; and physical effects such as diffraction, aberrations, and material interactions become more pronounced [83–85]. Traditional approaches attempt to address these challenges primarily through hardware solutions—utilizing more expensive components, implementing complex optical designs, or incorporating specialized materials. However, these approaches often result in systems that are costly, bulky, and impractical for many applications.

Differentiable imaging transforms this paradigm by enabling high-quality, cost-effective solutions through sophisticated modeling and reconstruction algorithms. Rather than requiring perfect optical components, this approach leverages computational techniques to compensate for hardware limitations. Recent advances demonstrate this capability across multiple spectral domains.

In extreme ultraviolet (EUV) lithography inspection, wavelength-multiplexed reflection ptychography has been developed to enable high-resolution imaging of semiconductor wafer nanostructures while addressing experimental uncertainties such as source instabilities and optical misalignments. This approach achieves a diffraction-limited resolution of 50 nm and establishes ptychography as a robust metrology tool for characterizing 3-dimensional nanostructures and EUV optics in industrial applications [86]. For infrared microscopy, differentiable Fourier ptychographic techniques have been implemented to overcome limited detector dynamic range and thermal noise issues, achieving high-quality reconstructions even with low-cost, off-the-shelf optical components [87,88]. In x-ray imaging, multi-slice wave propagation models incorporated in differentiable frameworks have addressed depth of focus limitations and scattering effects [60], while terahertz imaging has benefited from computational super-resolution with physics-informed priors to overcome limited spatial resolution and diffraction effects [84].

The ability to compensate for hardware limitations represents a fundamental shift in imaging system design philosophy. Rather than requiring ever more precise and expensive optical components, differentiable imaging enables robust performance with more practical hardware implementations, thus reducing system cost through the utilization of less expensive components, increasing system robustness by accommodating real-world imperfections, expanding application domains by enabling imaging in challenging environments, and democratizing access to advanced imaging capabilities that would otherwise require specialized facilities.

Synthesis beyond traditional constraints

The combination of extended capabilities and hardware compensation enables differentiable imaging to transcend traditional constraints in imaging system design. Conventional approaches typically necessitate compromises between performance metrics such as resolution, field of view, acquisition speed, and system complexity. Differentiable imaging redefines these relationships by jointly optimizing physical and computational aspects of the imaging system. This synthesis enables novel operational modes that would be unattainable through traditional methods. For example, spectral–temporal computational imaging systems can achieve snapshot multidimensional imaging by combining coded apertures with differentiable reconstruction algorithms [8]. Similarly, phase imaging systems can extract quantitative measurements from simple intensity-only detectors through differentiable wave propagation models.

As differentiable imaging continues to advance, further dissolution of traditional boundaries between imaging modalities, sensing approaches, and application domains can be anticipated. The framework's ability to bridge physical and computational aspects creates an expanded design space where system capabilities are constrained less by hardware limitations and more by algorithmic innovation and theoretical understanding of imaging processes.

Challenges and Opportunities

The transition from theoretical framework to practical implementation in differentiable optical imaging presents substantial challenges. The efficacy of this approach fundamentally depends on 2 critical capabilities: precise characterization of optical systems and effective solution of the inverse problem.

Numerical modeling

Differentiable optical imaging requires transforming complex physical phenomena into computationally tractable optimization problems. This transformation necessitates a delicate balance between physical fidelity and computational efficiency.

Different imaging modalities present distinct modeling requirements. X-ray imaging systems demand detailed models of radiation interaction with various materials, while coherent imaging systems must account for wave propagation effects and phase stability. Each application requires carefully calibrated physical detail in its mathematical representation. Uncertainty management represents another fundamental challenge. The definition of uncertainty bounds involves an inherent trade-off: overly expansive uncertainty sets may yield excessively conservative solutions, while insufficiently comprehensive sets may produce solutions lacking real-world robustness. Mathematical frameworks must maintain physical accuracy while operating within computational constraints. This becomes particularly demanding in multi-physics systems where various phenomena interact in complex ways. For example, thermal imaging systems require modeling both optical properties and their temperature dependence, creating interrelated physical relationships that must be accurately represented. Several mathematical approaches exist for addressing system uncertainties. Optimization strategies may focus on expected measurement values, consider measurement variance, evaluate statistical feasibility, or combine these approaches for enhanced robustness. Each method represents a different balance between performance optimization and operational reliability.

The integration of machine learning with physical modeling, illustrated in Fig. 4, presents a spectrum of implementation strategies. Purely data-driven methods offer flexibility but may lack physical consistency, while physics-informed approaches balance empirical learning with physical constraints. Structured methods enforce strict physical principles but may sacrifice adaptability. The optimal approach depends on specific application requirements and confidence in the underlying physical models.

Computational frameworks have substantially advanced the implementation of differentiable imaging systems. Modern platforms including PyTorch, TensorFlow, JAX, MATLAB, and Julia offer sophisticated AD capabilities that significantly streamline development processes. These frameworks, originally designed for machine learning applications [89–92], enable efficient integration of numerical optimization with neural networks, accelerating research progress in this field. The primary challenge in differentiable imaging remains the development of appropriate physical models for optical systems, which requires substantial domain expertise regardless of the availability of sophisticated AD frameworks. This challenge lies not in gradient computation mechanics but in designing accurate forward models that capture essential physics while remaining computationally tractable. Such models must properly address system-specific constraints, non-idealities, and parameter representations unique to optical systems. Many specialized optical phenomena necessitate custom differentiable implementations that extend beyond standard AD toolbox capabilities. Researchers frequently develop specialized gradient operations for application-specific optical components. In these contexts, integrated knowledge of both optical physics and computational methods remains essential for successful implementation. A particular challenge arises when incorporating non-differentiable operators into these frameworks. Different AD toolboxes offer varying solutions to this problem, with 4 primary approaches emerging in the literature: (a) custom gradient definitions that implement manual calculations for operations not supported by AD frameworks; (b) surrogate functions that replace non-differentiable operations with differentiable approximations; (c) smoothing approximations that introduce controlled approximations maintaining essential behavior while enabling gradient flow; and (d) sub-gradient methods that leverage concepts from non-smooth optimization theory. The selection of an appropriate strategy depends on both the specific non-differentiable operation and the AD framework being utilized, with each approach offering different trade-offs between implementation complexity and physical accuracy.

Black-box ML	Physics-informed ML	Structured ML
$\arg\min_{\theta} \|f_\theta(\mathbf{x}) - \mathbf{y}\|^2$	$\arg\min_{\theta} \|f_\theta(\mathbf{x}) - \mathbf{y}\|^2 + \lambda\|\mathcal{L}(f_\theta(\mathbf{x}))\|^2$	$\arg\min_{\theta} \|f_\theta(\mathbf{x}) - \mathbf{y}\|^2$ s.t. $\mathcal{L}(f_\theta(\mathbf{x})) = 0$
Pure data fitting	Physics as soft constraints	Physics as hard constraints

Fig 4. Transition from data-driven learning to physical constraints. $\mathcal{L}$: Physical operator; λ: Weight for physics constraints.

Computational efficiency

Modern imaging systems face increasingly complex computational challenges stemming from both the volume of data they generate and the sophistication of algorithms needed to process this information. The computational demands arise primarily from their ability to capture extraordinarily rich datasets. Consider hyperspectral imaging systems collecting information across numerous wavelengths, or time-resolved measurements tracking rapid changes in a sample. These advanced modalities generate massive, high-dimensional datasets that push well beyond what conventional processing approaches can handle efficiently.

This inherent complexity is further amplified by the need for system-specific algorithms. Each imaging system has its own unique characteristics—particular optical aberrations, specific sensor behaviors, and distinct environmental sensitivities. Our processing algorithms must account for all these factors while maintaining computational efficiency. For instance, an algorithm designed for a fluorescence microscope must consider not only the basic physics of light but also the specific behavior of the fluorophores, the characteristics of the optical filters, and any variations in detector sensitivity across the field of view.

Modern approaches to managing these computational challenges employ several sophisticated strategies. Compute Unified Device Architecture (CUDA)-based parallel processing architectures distribute calculations across multiple graphics processing unit (GPU) cores, enabling faster processing of large datasets. Memory-efficient algorithms carefully manage how data move through the system, minimizing bottlenecks and maximizing throughput. Looking toward the future, emerging technologies like photonic computing platforms and specialized on-chip solutions offer promising paths to achieving real-time processing capabilities even with complex datasets.

The integration of machine learning approaches introduces new possibilities for managing computational complexity, but also requires careful consideration of how we incorporate physical understanding into our systems. As shown in Fig. 4, when we use purely data-driven machine learning, we allow our algorithms to learn directly from the data without imposing physical constraints. This approach offers great flexibility but requires extensive high-quality training data and may struggle when confronted with scenarios that differ from its training examples.

Physics-informed machine learning takes a middle ground by incorporating physical laws as soft constraints during training. Rather than letting the algorithm learn purely from data, we guide it with our understanding of the physical world. This approach proves particularly valuable when working with limited or noisy data, as the physical constraints help prevent the system from learning incorrect patterns.

Structured machine learning represents the most physically constrained approach, requiring strict adherence to physical laws. While this ensures physically accurate results when our understanding of the system is complete, it may struggle to adapt to situations where our physical models are imperfect or when dealing with noisy real-world data.

One-way coupling and dynamic adaptation

Current differentiable imaging systems face a fundamental limitation in their operational architecture that significantly constrains their ability to respond to changing conditions. Despite sophisticated capabilities in modeling physical systems through differentiable components, most implementations operate in a unidirectional manner—information flows from the physical system to computational models, but rarely in the reverse direction in real time. This one-way coupling creates a static operational paradigm that fails to fully leverage the potential of differentiable frameworks.

The limitations of this unidirectional approach become particularly evident in dynamic imaging environments. Consider an adaptive optics microscopy system operating in a fluctuating thermal environment. As temperature variations induce optical misalignments and aberrations, a traditional differentiable imaging system can detect these changes through its measurements and potentially update its computational model. However, without a feedback mechanism to adjust physical parameters in real time, the system cannot actively compensate for these variations, leading to degraded performance until manual recalibration occurs. Similar challenges arise in numerous applications: multispectral imaging systems experiencing varying illumination conditions, medical imaging devices adapting to patient-specific characteristics, and remote sensing platforms subject to atmospheric turbulence. In each case, the inability to close the feedback loop between computational models and physical parameters prevents these systems from maintaining optimal performance in changing environments.

The theoretical foundation for bidirectional coupling already exists within the differentiable imaging framework. The optimization problem formulated in Eq. 2 simultaneously solves for both the imaged object $\mathbf{x}$ and system parameters $\boldsymbol{\theta}$. However, conventional implementations typically treat $\boldsymbol{\theta}$ as static once calibrated, rather than as dynamic variables that can be continuously updated and physically adjusted during operation. Emerging approaches to address one-way coupling operate across different timescales. At the fastest level, adaptive optics technologies like deformable mirrors can compensate for aberrations within milliseconds based on differentiable parameter estimates. At intermediate timescales, programmable elements such as digital micromirror devices and spatial light modulators adjust illumination patterns and phase profiles using computational feedback. For slower adaptations, robotic systems with motorized stages can reposition optical elements based on optimization results—particularly valuable in setups like ptychography where positioning precision directly affects reconstruction quality. The development of truly bidirectional differentiable imaging systems faces several technical challenges. First, physical actuators introduce their own uncertainties and limitations, which must be incorporated into the differentiable model. Second, real-time optimization becomes increasingly demanding as model complexity grows, requiring efficient algorithms and computational architectures. Third, stability considerations become crucial in closed-loop systems, where feedback between physical and computational components could potentially lead to oscillations or divergent behavior.

Despite these challenges, the potential benefits of bidirectional coupling are substantial. Systems capable of autonomous adaptation could maintain optimal performance across diverse operating conditions, automatically compensate for aging components or environmental variations, and even reconfigure themselves for different imaging tasks. This evolution toward adaptive, self-optimizing imaging platforms represents a natural progression of the differentiable imaging paradigm, extending its impact from design-time optimization to continuous operation-time adaptation.

Holistic optimization requirements

Computational imaging has evolved from simple digital capture to sophisticated systems that merge optical physics, electronic sensing, and computational processing. The fundamental challenge lies in capturing high-dimensional optical information—including spatial, spectral, temporal, and polarization data—using lower-dimensional measurements, typically on 2-dimensional (2D) sensor arrays [8]. While traditional approaches treated optical design, sensor development, and algorithmic processing as separate domains, modern systems demand integrated optimization across all components.

This integration is driven by several key factors. First, the optical data cube contains far more information than can be captured in a single exposure. As demonstrated throughout imaging applications from spectral imaging to temporal capture, successful system design requires careful selection of sampling strategies across the data dimensions. These strategies include temporal scanning, spatial multiplexing, and coded aperture techniques that enable compression of high-dimensional data onto 2D sensors.

Second, manufacturing and practical implementation constraints significantly impact system performance. While theoretical designs may approach fundamental limits, real-world systems must contend with fabrication tolerances, alignment precision, and environmental variations. Recent advances in metasurface optical elements provide unprecedented control over light's properties [93–95], but maximizing their capabilities requires optimization within the complete system context. By incorporating fabrication constraints directly into the design process through differentiable programming [96], we can better bridge the gap between theoretical capabilities and practical implementations.

Third, modern computational imaging systems increasingly rely on sophisticated machine learning algorithms for reconstruction and analysis. These algorithms must be considered during the optical design phase to ensure that the captured data enable reliable estimation of desired object properties. The emergence of differentiable imaging pipelines allows end-to-end optimization of optical, electronic, and computational components. While theoretical designs may achieve performance limits [97,98], practical systems require careful balance of resolution, speed, and computational complexity. The optimization challenge thus becomes inherently multidimensional [50]. Physical constraints include system size, power consumption, and thermal management. Computational requirements span real-time processing capabilities, memory limitations, and algorithm complexity. Application-specific demands further constrain the design space—medical imaging requires exceptional accuracy, industrial systems must operate in harsh environments, and research platforms need flexibility for exploring new modalities.

The optimization challenge becomes multidimensional, requiring careful balance of competing objectives [50]. At the physical level, we must simultaneously optimize system size, power consumption, and thermal management while maintaining optical performance. The integration of optical computing further complicates this balance, demanding seamless interaction between optical and electronic processing domains.

This holistic perspective represents a fundamental shift from traditional sequential optimization approaches. Rather than designing optical components first and then developing computational processing, modern systems require frameworks that simultaneously optimize physical, computational, and application-specific elements. Success in this domain requires new design tools that can handle the complete system complexity while producing practically implementable solutions.

Future Directions and Outlook

The evolution of differentiable optical imaging marks a transformative shift in computational imaging, fundamentally changing how we approach system design, optimization, and control. This framework's ability to bridge the gap between physical reality and computational models through rigorous mathematical formulations opens several promising pathways for future development.

Digital twin-equipped computational imaging

As computational imaging systems grow increasingly sophisticated, managing their complexity demands new approaches that bridge the gap between physical hardware and computational models. Digital twin technology, though not yet fully explored in imaging applications, offers intriguing possibilities for dynamic monitoring, optimization, and prediction of system behavior. Differentiable imaging provides a natural foundation for this integration [19]. Its ability to work with generic computer programs and combine different mathematical formalisms enables joint optimization of both inverse problems and system design. This flexibility, coupled with the capacity to leverage off-the-shelf machine learning frameworks, creates a powerful platform for addressing challenges across multiple scales.

Brief introduction of digital twin

The concept of digital twins emerged from a practical need to solve complex engineering challenges. During the space programs in the 1960s, NASA faced a critical problem: how to diagnose and fix spacecraft issues when the physical system was thousands of miles away. Their solution—creating exact physical duplicates for ground-level testing and simulation—proved invaluable during the Apollo 13 mission, when these replicas helped engineers solve life-threatening problems aboard the spacecraft [99]. A transformative shift occurred in 2002 when Dr. Michael Grieves proposed replacing physical duplicates with digital counterparts [100]. This initial concept evolved significantly through subsequent developments [101–103], marking the birth of modern digital twin technology and fundamentally changing how we approach system monitoring and optimization. As technology has advanced, digital twins have evolved far beyond simple virtual models. Today's digital twins integrate real-time data collection through Internet of Things devices, sophisticated simulation models, and predictive analytics powered by machine learning algorithms [104]. This combination enables capabilities that would have been impossible with physical duplicates: real-time monitoring across multiple parameters, predictive maintenance that anticipates failures before they occur, and dynamic optimization that continuously improves system performance [105,106]. The impact of digital twins has transformed numerous complex engineering domains [107–109]. In aerospace, manufacturers leverage digital twins to monitor and optimize aircraft performance throughout their operational life cycle [110,111], while manufacturing plants use them to streamline production and predict maintenance needs [106]. The technology has enabled ambitious projects like Nvidia's Earth-2, which aims to create a digital twin of our entire planet [112,113], demonstrating its potential to address challenges at unprecedented scales. In precision engineering, digital twins enable real-time metrology [108], and in photonics and optics, they advance innovation while optimizing performance and production costs [114].

Digital twin-equipped computational imaging

The growing complexity of computational imaging systems has revealed an urgent need for holistic optimization approaches. While differentiable imaging has made substantial advances in addressing system-wide optimization challenges, the requirement for adaptive and dynamic system monitoring remains. Digital twin technology, with its proven success in other domains, offers complementary capabilities that could address these remaining challenges.

A proposed framework, illustrated in Fig. 5, would establish bidirectional communication between physical and virtual domains through differentiable modeling. Such a system might comprise 2 main components: a physical counterpart handling data acquisition and control, and a virtual counterpart utilizing differentiable models for system optimization and parameter quantification. The physical twin would generate measurements through the mapping:

$$\mathbf{y}_p = f_p\left(\mathbf{x}, \boldsymbol{\theta}_p\right) \tag{3}$$

where f_p represents the physical system model with inherent uncertainties from environmental and systemic interactions. In parallel, the Virtual Digital Twin would aim to emulate this physical system through differentiable components:

$$\mathbf{y}_v = f\left(\mathbf{x}, \boldsymbol{\theta}_v\right) \tag{4}$$

Here, f represents interconnected subsystem models based on physical principles, with virtual parameters $\boldsymbol{\theta}_v$ that may deviate from physical parameters due to systemic uncertainties. This framework could enable system refinement through 2 processes. State estimation might determine virtual parameters $\boldsymbol{\theta}_v(t)$ at time t through optimization:

$$\boldsymbol{\theta}_v(t) = \arg\min_{\boldsymbol{\theta}_v} \left| f\left(\mathbf{x}, \boldsymbol{\theta}_v\right) - \mathbf{y}_p \right|^2 + \lambda \mathcal{R}\left(\boldsymbol{\theta}_v\right) \tag{5}$$

Model predictive control could then optimize control signals based on predicted behavior:

$$\mathbf{u}^*(t) = \arg\ \min\mathbf{u} \sum_{n=0}^{N} \left| \boldsymbol{\theta}_p(t+n) - \boldsymbol{\theta}_v(t+n) \right|^2 + |\mathbf{u}(t+n)|^2 \tag{6}$$

with parameter evolution following:

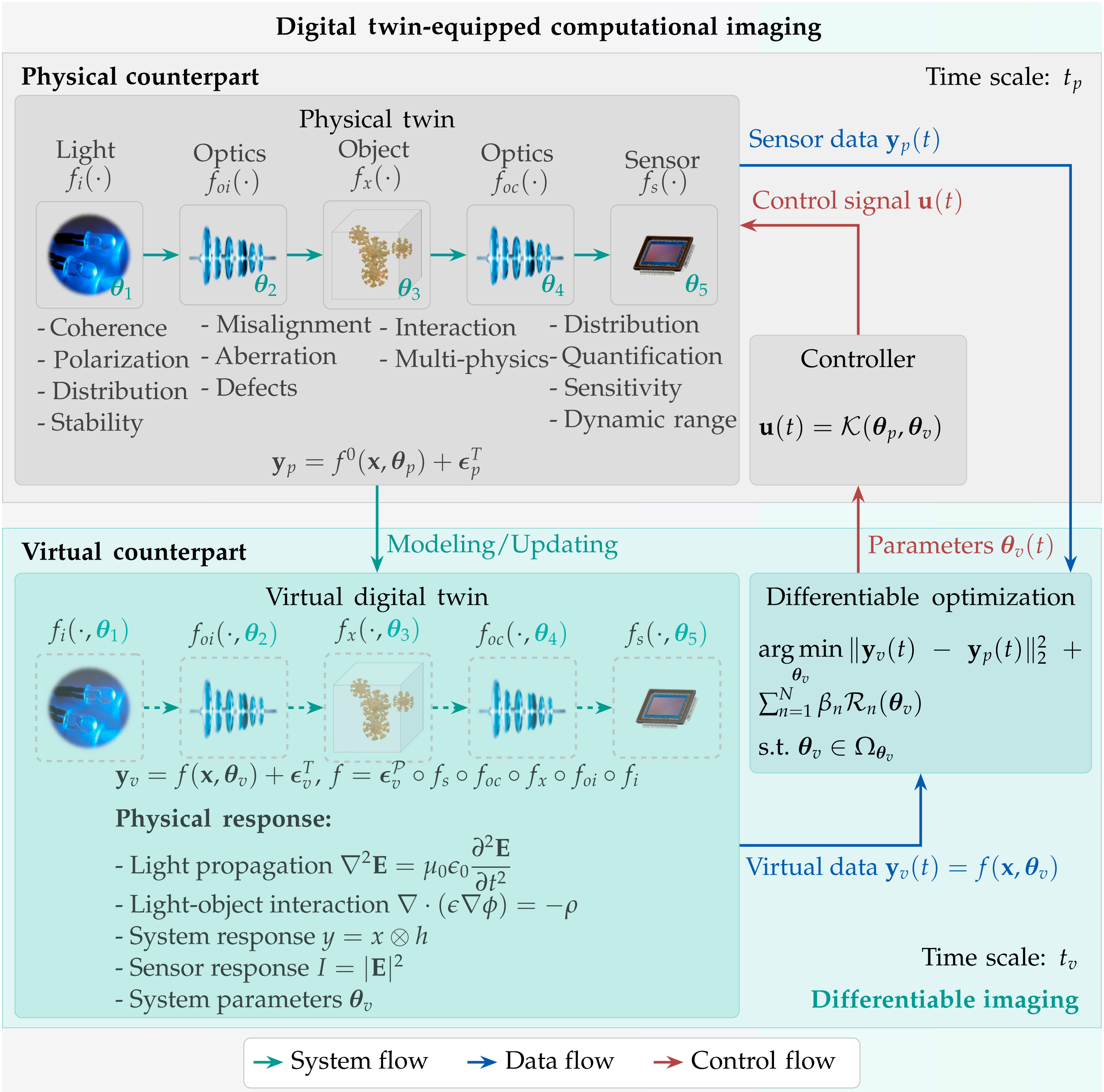

Fig 5. Schematic of digital twin-equipped computational imaging.

$$\boldsymbol{\theta}_p(t+n+1) = \boldsymbol{\theta}_p(t+n) + \mathbf{u}(t+n)\Delta t + \mathbf{w}(t+n) \quad (7)$$

where $\mathbf{w}(t+n)$ represents process noise capturing statistical uncertainties.

This framework demonstrates particular synergy with adaptive optics systems. While adaptive optics provides rapid physical wavefront correction through real-time feedback loops, digital twins enable predictive optimization and control across longer timescales. The integration creates a multi-timescale optimization approach: digital twins reduce system latency through predictive modeling and parameter optimization, while adaptive optics provides high-speed measurement data for model refinement. This combination enables robust imaging systems capable of handling complex dynamic environments while maintaining optimal performance.

Enhanced capabilities and applications

Digital twin-equipped computational imaging extends beyond basic system modeling to enable several advanced capabilities. First, it facilitates automated calibration processes that continuously refine system parameters during operation, eliminating the need for frequent manual recalibration and enabling deployment in less controlled environments. This is particularly valuable in field applications such as remote sensing, astronomical observation, and portable medical imaging where environmental conditions fluctuate unpredictably. Second, digital twins enable predictive maintenance by monitoring degradation patterns in optical elements, sensors, and mechanical components. The system can identify early indicators of performance deterioration before they manifest in image quality, allowing for scheduled maintenance rather than reactive repairs. For instance, in high-precision microscopy or industrial inspection systems, the digital twin can detect subtle changes in illumination uniformity or optical transmission that might indicate component aging. Third, these systems excel at anomaly detection and fault diagnosis. By continuously comparing measured data with predicted outputs, digital twins can identify unexpected deviations that may indicate hardware malfunctions, environmental interference, or novel phenomena of scientific interest. This capability proves particularly valuable in autonomous imaging systems deployed in remote or hazardous environments.

Implementation considerations

Successfully implementing digital twin-equipped computational imaging requires addressing several key considerations. The fidelity of the virtual twin depends critically on the accuracy of underlying physical models. These models must balance computational efficiency with physical accuracy, particularly for real-time applications. Differentiable physics-based models provide an ideal foundation, as they enable efficient parameter updates while maintaining physical consistency. The communication framework between physical and virtual twins represents another important consideration. This bidirectional data exchange must operate with minimal latency while handling potentially large volumes of image data and parameter updates. Edge computing architectures that distribute processing between local hardware and centralized resources can optimize this communication, particularly for resource-constrained mobile imaging systems. Uncertainty management presents a third critical consideration. Both measurement uncertainty in the physical system and modeling uncertainty in the virtual twin must be quantified and propagated through the control loop. Bayesian approaches that maintain probability distributions over system parameters offer a principled framework for decision-making under uncertainty, enabling robust performance even when faced with incomplete or noisy measurements.

Emerging applications

Several emerging application domains stand to benefit significantly from digital twin-equipped computational imaging. In medical imaging, digital twins could enable personalized imaging protocols that adapt to individual patient characteristics and clinical objectives. By maintaining patient-specific models that account for anatomical variations and tissue properties, these systems could optimize acquisition parameters to minimize radiation dose or contrast agent requirements while maximizing diagnostic information. In optical microscopy, digital twins could transform live-cell imaging by predicting and compensating for phototoxicity and photobleaching effects. The virtual twin could model the photochemical response of fluorophores and cellular structures, enabling intelligent illumination strategies that preserve sample viability while capturing critical biological dynamics. Space-based observation systems represent another promising application domain. Here, digital twins could compensate for the harsh operating environment and limited maintenance opportunities by continuously adapting to radiation damage, thermal fluctuations, and mechanical wear. This would extend the effective lifetime of these costly instruments and maintain scientific productivity throughout their operational lifespan. Industrial machine vision systems could leverage digital twins to adapt to changing production conditions and materials. The virtual twin would model interactions between illumination, materials, and imaging optics, enabling robust inspection performance despite variations in product appearance, lighting conditions, or camera positioning.

Integration with differentiable imaging

The synergy between differentiable imaging and digital twins creates a particularly powerful framework for computational imaging. Differentiable imaging provides the mathematical foundation for efficiently updating the virtual twin based on measured data, while digital twins extend differentiable imaging with temporal modeling and predictive capabilities. This integration enables joint optimization across multiple timescales: differentiable imaging optimizes the fundamental system design and reconstruction algorithms, while digital twins handle dynamic adaptation during operation. Together, they create imaging systems that not only perform optimally under nominal conditions but also adapt intelligently to changing environments, aging components, and evolving application requirements. As computational resources continue to advance, we anticipate increasingly sophisticated digital twin implementations that incorporate multi-physics modeling, real-time uncertainty quantification, and learning-based adaptation. This evolution will further enhance the robustness and capability of computational imaging systems across scientific, medical, and industrial applications.

Emerging opportunities

The evolution of differentiable optical imaging marks a transformative shift in computational imaging, fundamentally changing how we approach system design, optimization, and control. This framework's power lies in its ability to bridge the gap between physical reality and computational models through rigorous mathematical formulations and comprehensive uncertainty handling. Looking ahead, several promising pathways could further transform imaging system design and implementation.

Technical advances and innovation

The integration of advanced manufacturing techniques with differentiable optimization opens new possibilities in system design. By incorporating computational models directly into the physical fabrication process, we can optimize entire systems while accounting for real-world manufacturing constraints and tolerances. This integrated approach enables the development of hybrid optical–electronic systems that leverage the strengths of both domains. The framework enables entirely new approaches to imaging itself. Multi-modal imaging systems can now effectively combine different contrast mechanisms, providing richer information about specimens than previously possible. Through real-time optimization of system configurations, these adaptive imaging systems can respond dynamically to changing experimental conditions and requirements.

Enhanced experimental capabilities

Differentiable imaging is revolutionizing experimental protocols through sophisticated data-driven optimization. Instead of relying on fixed measurement sequences, advanced sampling strategies can now adapt in real time based on the information content of each measurement. This dynamic approach enables imaging systems to continuously adjust their parameters based on current observations, ensuring optimal performance even as conditions change. These capabilities prove particularly valuable in complex imaging applications where traditional fixed protocols might miss crucial information or waste resources on redundant measurements.

Theoretical challenges and opportunities

The future advancement of differentiable imaging requires addressing several key theoretical challenges. Current models must extend to incorporate quantum effects and nonlinear phenomena, enabling more accurate system representations. We need more efficient optimization algorithms capable of handling high-dimensional parameter spaces without becoming trapped in local minima. The field needs unified frameworks that can bridge multiple physical domains, facilitating more comprehensive system design and analysis. At a more fundamental level, we must consider whether computational imaging might help us exceed traditional optical system limits. The question of achieving true holistic optimization—considering physical, computational, and application-specific requirements simultaneously—remains a substantial challenge that requires innovative solutions.

Path forward

The impact of differentiable imaging extends significantly beyond technical improvements to enable transformative approaches to scientific discovery. The framework permits automated hypothesis generation and testing through differentiable physical models, potentially accelerating research processes across multiple disciplines. Through systematic exploration of parameter spaces that would be intractable with traditional methods, researchers can discover new physical phenomena that might otherwise remain undetected. The integration of physical understanding with data-driven insights creates powerful new tools for scientific investigation that maintain interpretability while leveraging computational efficiency.

Differentiable imaging provides substantial advantages to artificial intelligence (AI) for science initiatives by establishing a robust bridge between first-principles physics and data-driven discovery. By embedding physical laws directly into differentiable computational frameworks, it enables scientists to develop models that maintain physical consistency while harnessing the optimization capabilities of machine learning techniques. This integration addresses several critical challenges in scientific AI applications: it substantially reduces data requirements compared to purely data-driven approaches—a substantial advantage in scientific domains where high-quality labeled data are scarce or prohibitively expensive; it maintains interpretability by preserving the physical meaning of parameters throughout the optimization process; and it facilitates rigorous uncertainty quantification that adheres to scientific standards.

In fields such as molecular imaging, material characterization, and astronomical observation, differentiable imaging has demonstrated remarkable capabilities in extracting meaningful insights from noisy, incomplete data while maintaining physical realism. By enabling end-to-end optimization of entire experimental pipelines—from instrument design through data acquisition to analysis—differentiable imaging allows AI for science to operate across traditional disciplinary boundaries, potentially revealing previously inaccessible phenomena. As scientific discovery increasingly relies on computational methods to interpret complex experimental data, differentiable imaging's capacity to maintain physical consistency while adapting to empirical evidence positions it as an essential methodology for advancing AI for science initiatives.

The continued evolution of computational capabilities, coupled with advances in machine learning and optimization algorithms, suggests a promising future for differentiable imaging applications. As these technologies mature, we anticipate breakthrough applications across diverse fields ranging from biological imaging to industrial inspection and quality control. Alongside the potential of digital twins discussed previously, these developments collectively indicate a future where imaging systems become increasingly sophisticated, adaptive, and capable of addressing complex scientific challenges that currently remain beyond reach.

The key to realizing this potential lies in developing unified approaches that seamlessly integrate physical understanding, computational optimization, and real-world applications. While substantial challenges remain in areas such as computational efficiency, model fidelity, and system integration, the foundation established by differentiable imaging and the promise of digital twin integration suggest a transformative path forward for computational imaging science. The convergence of these methodologies may enable new generations of imaging systems that not only capture but also interpret and analyze complex phenomena, fundamentally changing how we observe and understand the world around us.

Conclusion

The emergence of differentiable imaging represents a paradigm shift in computational imaging, fundamentally redefining how we conceptualize, design, and optimize imaging systems. By bridging the persistent gap between physical reality and computational models through end-to-end differentiable frameworks, this approach enables unprecedented capabilities in addressing system uncertainties, optimizing complex optical setups, and expanding imaging capabilities beyond traditional limitations.

Throughout this review, we have demonstrated how differentiable imaging excels in 3 critical dimensions. First, it systematically addresses physical–numerical model mismatches—both deterministic uncertainties, like alignment errors and manufacturing tolerances, and stochastic uncertainties, such as sensor noise and environmental variations. Second, it enables true system co-design by simultaneously optimizing optical and computational elements as an integrated system rather than separate components. Third, it extends imaging capabilities while compensating for hardware limitations, democratizing access to advanced imaging techniques that would otherwise require prohibitively expensive equipment.

As we look to the future of this rapidly evolving field, several fundamental research directions emerge. The integration of differentiable imaging with digital twin technology presents a particularly promising frontier, potentially enabling real-time system monitoring, predictive maintenance, and adaptive optimization across multiple timescales. This integration could transform imaging systems from static instruments into dynamic, self-optimizing platforms that continuously adapt to changing conditions and requirements.

Theoretical advances are needed to extend current differentiable frameworks to incorporate quantum effects, nonlinear phenomena, and multi-physics interactions that characterize complex imaging scenarios. More efficient optimization algorithms capable of navigating high-dimensional parameter spaces without becoming trapped in local minima will be crucial for realizing the full potential of differentiable imaging in practical applications.

The growing convergence between differentiable imaging and AI for science initiatives offers exciting possibilities for scientific discovery. By embedding physical laws directly into differentiable computational frameworks, these approaches enable the development of models that maintain physical consistency while leveraging the power of machine learning optimization. This integration significantly reduces data requirements compared to purely data-driven approaches—a critical advantage in scientific domains where high-quality labeled data are scarce—while maintaining interpretability and enabling rigorous uncertainty quantification.

Perhaps the most profound question facing differentiable imaging is whether it might help us exceed traditional limits in optical system performance. By holistically optimizing across physical, computational, and application-specific dimensions simultaneously, differentiable frameworks may uncover novel system configurations that transcend conventional design paradigms.

Ultimately, differentiable imaging represents not merely a technical advancement but a fundamental reconceptualization of imaging science itself. As this field continues to mature, we anticipate a new generation of imaging systems that combine physical accuracy with computational efficiency, that adapt intelligently to changing conditions, and that push the boundaries of what we can observe and measure about the world around us. The methodologies and principles discussed in this review provide a foundation for researchers and practitioners working to realize this vision across scientific, medical, industrial, and consumer applications.

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References

1. Mait JN, Euliss GW, Athale RA. Computational imaging. *Adv Opt Photon*. 2018;10(2):409–483.
2. Barbastathis G, Ozcan A, Situ G. On the use of deep learning for computational imaging. *Optica*. 2019;6(8):921–943.
3. Wu J, Zhang H, Zhang W, Jin G, Cao L, Barbastathis G. Single-shot lensless imaging with Fresnel zone aperture and incoherent illumination. *Light Sci Appl*. 2020;9:53.
4. Brady DJ, Gehm ME, Stack RA, Marks DL, Kittle DS, Golish DR, Vera EM, Feller SD. Multiscale gigapixel photography. *Nature*. 2012;486:386–389.
5. Boominathan V, Robinson JT, Waller L, Veeraraghavan A. Recent advances in lensless imaging. *Optica*. 2021;9(1):1–6.
6. Ozcan A, McLeod E. Lensless imaging and sensing. *Annu Rev Biomed Eng*. 2016;18:77–102.
7. Wang Z, Peng Y, Fang L, Gao L. Computational optical imaging: On the convergence of physical and digital layers. *Optica*. 2025;12(1):113–130.
8. Brady DJ. *Computational optical imaging*. SPIE Press; 2025.
9. Zhou A, Wang W, Chen N, Lam EY, Lee B, Situ G. Fast and robust misalignment correction of Fourier ptychographic microscopy for full field of view reconstruction. *Opt Express*. 2018;26(18):23661–23674.
10. Jiang S, Song P, Wang T, Yang L, Wang R, Guo C, Feng B, Maiden A, Zheng G. Spatial- and Fourier-domain ptychography for high-throughput bio-imaging. *Nat Protoc*. 2023;18:2051–2083.
11. Du M, Zhou T, Deng J, Ching DJ, Henke S, Cherukara MJ. Predicting ptychography probe positions using single-shot phase retrieval neural network. *Opt Express*. 2024;32(21):36757–36780.
12. Zheng G, Horstmeyer R, Yang C. Wide-field, high-resolution Fourier ptychographic microscopy. *Nat Photonics*. 2013;7:739–745.
13. Bioucas-Dias JM, Plaza A, Camps-Valls G, Scheunders P, Nasrabadi N, Chanussot J. Hyperspectral remote sensing data analysis and future challenges. *IEEE Geosci Remote Sens Mag*. 2013;1:6–36.
14. Velten A, Willwacher T, Gupta O, Veeraraghavan A, Bawendi MG, Raskar R. Recovering three-dimensional shape around a corner using ultrafast time-of-flight imaging. *Nat Commun*. 2012;3:745.
15. Raissi M, Perdikaris P, Karniadakis G. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *J Comput Phys*. 2019;378:686–707.
16. Zheng G, Shen C, Jiang S, Song P, Yang C. Concept, implementations and applications of Fourier ptychography. *Nat Rev Phys*. 2021;3:207–223.
17. Jurling AS, Fienup JR. Applications of algorithmic differentiation to phase retrieval algorithms. *J Opt Soc Am A*. 2014;31(7):1348–1359.
18. Herath K, Haputhanthri U, Hettiarachchi R, Kariyawasam H, Ahmad R, Ahmad A, Ahluwalia B, Edussooriya C, Wadduwage D. Differentiable microscopy designs an all optical quantitative phase microscope. arXiv. 2023. https://doi.org/10.48550/arXiv.2203
19. Chen N, Cao L, Poon TC, Lee B, Lam EY. Differentiable imaging: A new tool for computational optical imaging. *Adv Phys Res*. 2023;2(6):2200118.
20. Gupta S, Kothari K, Debarnot V, Dokmanic I. Differentiable uncalibrated imaging. *IEEE Trans Comput Imaging*. 2024;10:1–16.
21. Thies M, Wagner F, Huang Y, Gu M, Kling L, Pechmann S, Aust O, Grüneboom A, Schett G, Christiansen S, et al. Calibration by differentiation—Self-supervised calibration for X-ray microscopy using a differentiable cone-beam reconstruction operator. *J Microsc*. 2022;287(2):81–92.
22. Dufraisse M, Trouve-Peloux P, Volatier JB, Champagnat F. On the use of differentiable optical models for lens and neural

network co-design. In: Georges MP, Popescu G, Verrier N, editors. *Unconventional optical imaging III*. SPIE; 2022. Vol. 12136, p. 164–173.
23. Hernandez A, Millerioux G, and Amigo JM. Differentiable programming: Generalization, characterization and limitations of deep learning. arXiv. 2022. https://doi.org/10.48550/arXiv.2205.06898
24. Li TM, Gharbi M, Adams A, Durand F, Ragan-Kelley J. Differentiable programming for image processing and deep learning in halide. *ACM Trans Graph*. 2018;37:1–13.
25. Trusiak M, Picazo-Bueno JA, Zdankowski P, Mico V. DarkFocus: Numerical autofocusing´ in digital in-line holographic microscopy using variance of computational dark-field gradient. *Opt Lasers Eng*. 2020;134:Article 106195.
26. Wu Y, Lu L, Zhang J, Li Z, Zuo C. Autofocusing algorithm for pixel-super-resolved Lensfree on-Chip microscopy. *Front Phys*. 2021;9: doi.org/10.3389/fphy.2021.651316.
27. Wu Z, Chen G, Liu S, Liu W, Chi D, Gao B, Li Y, Liu Z. Four-frame pixel super-resolution method for lensless imaging systems. *Opt Lasers Eng*. 2025;184:Article 108597.
28. Zhang J, Sun J, Chen Q, Li J, Zuo C. Adaptive pixel-super-resolved lensfree in-line digital holography for wide-field on-chip microscopy. *Sci Rep*. 2017;7(1):11777.
29. Wang J, Wu Y, Wang J, Chen N. Align-free multi-plane phase retrieval. *Opt Laser Technol*. 2025;181:Article 111784.
30. Sun J, Chen Q, Zhang Y, Zuo C. Efficient positional misalignment correction method for Fourier ptychographic microscopy. *Biomed Opt Express*. 2016;7(4):1336–1350.
31. Eckert R, Phillips ZF, Waller L. Efficient illumination angle self-calibration in Fourier ptychography. *Appl Opt*. 2018;57(19):5434–5442.
32. Yang D, Zhang S, Zheng C, Zhou G, Cao L, Hu Y, Hao Q. Fourier ptychography multi-parameter neural network with composite physical priori optimization. *Biomed Opt Express*. 2022;13:2739.
33. Zhou KC, Aidukas T, Loetgering L, Wechsler F, Horstmeyer R. Introduction to Fourier ptychography: Part I. *Microscopy Today*. 2022;30:36–41.
34. Konda PC, Loetgering L, Zhou KC, Xu S, Harvey AR, Horstmeyer R. Fourier ptychography: Current applications and future promises. *Opt Express*. 2020;28(7):9603–9630.
35. Loetgering L, Aidukas T, Zhou KC, Wechsler F, Horstmeyer R. Fourier ptychography part II: Phase retrieval and high-resolution image formation. *Microscopy Today*. 2022;30(5):36–39.
36. Xu F, Wu Z, Tan C, Liao Y, Wang Z, Chen K, Pan A. Fourier ptychographic microscopy 10 years on: A review. *Cells*. 2024;13(4):324.
37. McLeod E, Ozcan A. Microscopy without lenses. *Phys Today*. 2017;70(9):50–56.
38. Chen N, Wang C, Heidrich W. *∂H*: Differentiable holography. *Laser Photonics Rev*. 2023;17(9):2200828.
39. Chen N, Lam EY. Differentiable pixel-super-resolution lensless imaging. *Opt Lett*. 2025;50(4):1180–1183.
40. Zhou T, Cherukara M, Phatak C. Differential programming enabled functional imaging with Lorentz transmission electron microscopy. *NPJ Comput Mater*. 2021;7:141.
41. Du M, Kandel S, Deng J, Huang X, Demoetiere A, Nuguyen TT, Tucoulou R, De Andrade V, Jin Q, Jacobsen C. Adorym: A multi-platform generic X-ray image reconstruction framework based on automatic differentiation. *Opt Express*. 2021;29(7):10000–10035.
42. Nashed YS, Peterka T, Deng J, Jacobsen C. Distributed automatic differentiation for Ptychography. *Procedia Comput Sci*. 2017;108:404–414.
43. Seifert J, Bouchet D, Loetgering L, Mosk AP. Efficient and flexible approach to ptychography using an optimization framework based on automatic differentiation. *OSA Continuum*. 2021;4:121.
44. Ghosh S, Nashed YSG, Cossairt O, Katsaggelos A. ADP: Automatic differentiation ptychography. In: *2018 IEEE International Conference on Computational Photography (ICCP)*. IEEE; 2018. p. 1–10.
45. Kandel S, Maddali S, Allain M, Hruszkewycz SO, Jacobsen C, Nashed YSG. Using automatic differentiation as a general framework for ptychographic reconstruction. *Opt Express*. 2019;27(13):18653–18672.
46. Sun R, Yang D, Hu Y, Hao Q, Li X, Zhang S. Unsupervised adaptive coded illumination Fourier ptychographic microscopy based on a physical neural network. *Biomed Opt Express*. 2023;14(8):4205–4216.
47. Sun R, Yang D, Zhang S, Hao Q. Hybrid deep-learning and physics-based neural net-work for programmable illumination computational microscopy. *Adv Photonics Nexus*. 2024;3.
48. Chen N, Wu Y, Tan C, Cao L, Wang J, Lam EY. Uncertainty-aware Fourier ptychography. *Light: Science & Applications*; 2025.
49. Feng BY, Ferrer-Chavez R, Levis A, Wang JJ, Bouman KL, Freeman WT. Exoplanet imaging via differentiable rendering. *IEEE Trans Comput Imaging*. 2025;11:36–51.
50. Kochenderfer MJ. Wheeler TA, editor. *Algorithms for optimization*. Cambridge: The MIT Press; 2019.
51. Bian Z, Dong S, Zheng G. Adaptive system correction for robust Fourier ptychographic imaging. *Opt Express*. 2013;21(26):32400–32410.
52. Pan A, Zuo C, Xie Y, Lei M, Yao B. Vignetting effect in Fourier ptychographic microscopy. *Opt Lasers Eng*. 2019;120:40–48.
53. Wang T, Jiang S, Song P, Wang R, Yang L, Zhang T, Zheng G. Optical ptychography for biomedical imaging: Recent progress and future directions [invited]. *Biomed Opt Express*. 2023;14(2):489–532.
54. Zhang S, Berendschot TT, Zhou J. ELFPIE: An error-laxity Fourier ptychographic iterative engine. *Signal Process*. 2023;210:Article 109088.
55. Zhang S, Wang A, Xu J, Feng T, Zhou J, Pan A. FPM-WSI: Fourier ptychographic whole slide imaging via feature-domain backdiffraction. *Optica*. 2024;11(5):634–646.
56. Wu H, Wang J, Pan H, Lyu J, Zhang S, Zhou J. Wavelet-forward family enabling stitching-free full-field Fourier ptychographic microscopy. *Laser Photonics Rev*. 2024;19(3):2401183.
57. Brady DJ, Choi K, Marks DL, Horisaki R, Lim S. Compressive holography. *Opt Express*. 2009;17(15):13040–13049.
58. Chowdhury S, Chen M, Eckert R, Ren D, Wu F, Repina N, Waller L. High-resolution 3D refractive index microscopy of multiple-scattering samples from intensity images. *Optica*. 2019;6(9):1211–1219.
59. Chen M, Ren D, Liu HY, Chowdhury S, Waller L. Multi-layer born multiple-scattering model for 3D phase microscopy. *Optica*. 2020;7:394.
60. Du M, Nashed YSG, Kandel S, Gursoy D, Jacobsen C. Three dimensions, two microscopes, one code: Automatic differentiation for x-ray nanotomography beyond the depth of focus limit. *Sci Adv*. 2020;6(13):eaay3700.

61. Wu Y, Wang J, Thoroddsen ST, Chen N. Single-shot high-density volumetric particle imaging enabled by differentiable holography. *IEEE Trans Industr Inform*. 2024;20(12): 13696–13706.
62. Klauss A, Conrad F, Hille C. Binary phase masks for easy system alignment and basic aberration sensing with spatial light modulators in STED microscopy. *Sci Rep*. 2017;7:15699.
63. Shuang B, Wang W, Shen H, Tauzin LJ, Flatebo C, Chen J, Moringo NA, Bishop LDC, Kelly KF, Landes CF. Generalized recovery algorithm for 3D super-resolution microscopy using rotating point spread functions. *Sci Rep*. 2016;6:30826.
64. Zhao T, Mauger T, Li G. Optimization of wavefront-coded infinity-corrected microscope systems with extended depth of field. *Biomed Opt Express*. 2013;4(8):1464–1471.
65. Page J, Favaros P. Learning to model and calibrate optics via a differentiable wave optics simulator. In: *IEEE International Conference on Image Processing (ICIP)*. IEEE; 2020.
66. Sasian J. *Introduction to aberrations in optical imaging systems*. Cambridge University Press; 2012.
67. Sasian J. *Introduction to lens design*. Cambridge University Press; 2019.
68. Wang C, Chen N, Heidrich W. Towards self-calibrated lens metrology by differentiable refractive deflectometry. *Opt Express*. 2021;29(19):30284–30295.
69. Wang C, Chen N, Heidrich W. dO: A differentiable engine for deep lens design of computational imaging systems. *IEEE Trans Comput Imaging*. 2022;8:905–916.
70. Nimier-David M, Vicini D, Zeltner T, Jakob W. Mitsuba 2. *ACM Trans Graph*. 2019;38:1–17.
71. Jakob W, Speierer S, Roussel N, Vicini D. DR.JIT: A just-in-time compiler for differentiable rendering. A just-in-time compiler for differentiable rendering. *ACM Trans Graph*. 2022;41:1–19.
72. Ho CJ, Belhe Y, Rotenberg S, Ramamoorthi R, Li TM, Antipa N. A differentiable wave optics model for end-to-end imaging system optimization. arXiv. 2024. https://doi.org/10.48550/arXiv.2412.09774
73. Filipovich MJ, Lvovsky AI. TorchOptics: An open-source Python library for differentiable Fourier optics simulations. arXiv. 2024. https://doi.org/10.48550/arXiv.2411.18591
74. Tang H, Li H, Feng Z, Luo Y, Mao X. Differentiable design of a double-freeform lens with multi-level radial basis functions for extended source irradiance tailoring. *Optica*. 2024;11(5):653–664.
75. Zhou J, Chen B, Yan J, Ren Z, Zhang W, Feng H, Chen Y, Bian M. Optical degradation correction of manufacturing-perturbed glassplastic hybrid lens systems via a joint hardware-software optimization framework. *Opt Express*. 2024;32(15):25866–25882.
76. Sun Q, Wang C, Fu Q, Dun X, Heidrich W. End-to-end complex lens design with differentiate ray tracing. *ACM Trans Graph*. 2021;40:1–13.
77. Zhang W, Ren Z, Zhou J, Chen S, Feng H, Li Q, Xu Z, Chen Y. End-to-end automatic lens design with a differentiable diffraction model. *Opt Express*. 2024;32:44328.
78. Wang T, Wang J, Matsuda N, Cossairt O, Willomitzer F. Differentiable deflectometric eye tracking. *IEEE Trans Comput Imaging*. 2024;10:888–898.
79. Shi R, Zhang T, Zhou Y, Shao Y, Zhang H, Wei R, Bai J. End-to-end hybrid infrared imaging system design with thermal analysis. *Opt Express*. 2025;33(3):4011–4023.
80. Yang X, Fu Q, Heidrich W. Curriculum learning for ab initio deep learned refractive optics. *Nat Commun*. 2024;15:6572.
81. Song P, Jiang S, Zhang H, Huang X, Zhang Y, Zheng G. Full-field Fourier ptychography (FFP): Spatially varying pupil modeling and its application for rapid field-dependent aberration metrology. *APL Photonics*. 2019;4.
82. Aidukas T, Wechsler F, Loetgering L, Zhou K, Horstmeyer R. Applications and extensions of Fourier ptychography. *Microscopy Today*. 2022;30(6):40–45.
83. Dethlefsen M, Azhar M, Engel T, Abhijeet J, Paulicka P, Kollegal M, Marquardt G. UV-FPM for the label-free analysis of biological samples. In: Shaked NT, Hayden O, editors. *Label-free biomedical imaging and sensing (LBIS) 2023*. SPIE; 2023. p. 33.
84. Zhao Q, Wang R, Zhang S, Wang T, Song P, Zheng G. Deep-ultraviolet Fourier ptychography (DUV-FP) for label-free biochemical imaging via feature-domain optimization. *APL Photonics*. 2024;9:090801.
85. Park KS, Bae YS, Choi SS, Sohn MY. High numerical aperture reflective deep ultraviolet Fourier ptychographic microscopy for nanofeature imaging. *APL Photonics*. 2022;7:096105.
86. Shao Y, Weerdenburg S, Seifert J, Urbach HP, Mosk AP, Coene W. Wavelength-multiplexed multi-mode EUV reflection ptychography based on automatic differentiation. *Light Sci Appl*. 2024;13:196.
87. Chen N, Brady DJ. Slimming optical systems and boosting performance with differentiable programming. Paper presented at: 14th International Conference on Optics-Photonics Design and Fabrication (ODF'24); 2024; Tucson, AZ, USA.
88. Chen N, Brady DJ. Differentiable holography and its development. In: *Frontiers in Optics + Laser Science (FiO + LS) Congress*. Optica Publishing Group; 2024.
89. Abadi M, Agarwal A, Barham P, Brevdo E, Chen Z, Citro C, Corrado GS, Davis A, Dean J, Devin M, et al. TensorFlow: Large-scale machine learning on heterogeneous systems. 2015. https://www.tensorflow.org
90. Paszke A, Gross S, Massa F, Lerer A, Bradbury J, Chanan G, Killeen T, Lin Z, Gimelshein N, Antiga L, et al. PyTorch: An imperative style, high-performance deep learning library. arXiv. 2019. https://doi.org/10.48550/arXiv.1912.01703
91. Bezanson J, Edelman A, Karpinski S, Shah VB. Julia: A fresh approach to numerical computing. *SIAM Rev*. 2017;59:65–98.
92. Bradbury J, Frostig R, Hawkins P, Johnson MJ, Leary C, Maclaurin D, Necula G, Paszke A, VanderPlas J, Wanderman-Milneet S, et al. JAX: Composable transformations of python+NumPyprograms. Version 0.3.13. 2018. http://github.com/google/jax
93. Li L, Wang S, Zhao F, Zhang Y, Wen S, Chai H, Gao Y, Wang W, Cao L, Yang Y. Single-shot deterministic complex amplitude imaging with a single-layer metalens. *Sci Adv*. 2024;10(1):Article eadl0501.
94. Colburn S, Zhan A, Majumdar A. Metasurface optics for full-color computational imaging. *Sci Adv*. 2018;4(2): Article eaar2114.
95. Shanker A, Froch JE, Mukherjee S, Zhelyeznyakov M, Brunton SL, Seibel EJ, Majumdar A. Quantitative phase imaging endoscopy with a metalens. *Light: Science & Applications*; 2024: 13.
96. Zheng C, Zhao G, So P. Close the design-to-manufacturing gap in computational optics with a 'Real2Sim' learned two-photon neural lithography simulator. In: *SIGGRAPH Asia 2023 Conference Papers*. ACM; 2023. p. 1–9.

97. Schulz TJ, Brady DJ, Wang C. Photon-limited bounds for phase retrieval. *Opt Express*. 2021;29(11):16736–16748.
98. Chen N, Brady D. Ptychographic wavefront cameras. *Opt Lett*. 2024;49(23):6653–6656.
99. Kranz G. *Failure is not an option. Mission control from Mercury to Apollo 13 and beyond*. New York (NY): Thorndike Press; 2000.
100. Grieves MW. Completing the cycle: Using PLM information in the sales and service functions [slides]. In: *SME Management Forum*. 3/4. Inderscience Publishers; 2002. vol. 14, p. 180.
101. Grieves MW. Product lifecycle management: The new paradigm for enterprises. *Int J Prod Dev*. 2005;2:71.
102. Grieves M. Digital twin: Manufacturing excellence through virtual factory replication. *White Paper*. 2014;1:1–7.
103. Grieves M, Hua E.Y. Hua EY. Defining, exploring, and simulating the digital twin metaverses. In: *Digital twins, simulation, and the metaverse*. Springer Nature Switzerland; 2024. p. 1–31.
104. Tao F, Zhang H, Liu A, Nee AYC. Digital twin in industry: State-of-the-art. *IEEE Trans Industr Inform*. 2019;15:2405–2415.
105. Tao F, Cheng J, Qi Q, Zhang M, Zhang H, Sui F. Digital twin-driven product design, manufacturing and service with big data. *Int J Adv Manuf Technol*. 2017;94:3563–3576.
106. Negri E, Fumagalli L, Macchi M. A review of the roles of digital twin in CPS-based production systems. *Procedia Manuf*. 2017;11:939–948.
107. National Academy of Engineering; National Academies of Sciences, Engineering, and Medicine; Division on Engineering and Physical Sciences; Division on Earth and Life Studies; Board on Mathematical Sciences and Analytics; Committee on Applied and Theoretical Statistics; Computer Science and Telecommunications Board; Board on Life Sciences; Board on Atmospheric Sciences and Climate; Committee on Foundational Research Gaps and Future Directions for Digital Twins. *Foundational research gaps and future directions for digital twins*. National Academies Press; 2024.
108. Wright L, Davidson S. Digital twins for metrology; metrology for digital twins. *Meas Sci Technol*. 2024;35:Article 051001.
109. Hazeleger W, Aerts JPM, Bauer P, Bierkens MFP, Camps-Valls G, Dekker MM, Doblas-Reyes FJ, Eyring V, Finkenauer C, Grunder A, et al. Digital twins of the earth with and for humans. *Commun Earth Environ*. 2024;5.
110. Glaessgen E, Stargel D. The digital twin paradigm for future NASA and U.S. Air Force Vehicles. 2012.
111. Ferrari A, Willcox K. Digital twins in mechanical and aerospace engineering. *Nature Computat Sci*. 2024;4:178–183.
112. Kurth T, Subramanian S, Harrington P, Pathak J, Mardani M, Hall D, Miele A, Kashinath K, Anandkumar A. FourCastNet: Accelerating global high-resolution weather forecasting using adaptive Fourier neural operators. In: *Proceedings of the Platform for Advanced Scientific Computing Conference*. ACM; 2023. p. 1–11.
113. NVIDIA Corporation. NVIDIA Modulus: A Framework for Building Physics-ML Models. 2023. [accessed 2024-07-01] https://developer.nvidia.com/modulus
114. Guo Y, Klink A, Bartolo P, Guo WG. Digital twins for electro-physical, chemical, and photonic processes. *CIRP Ann*. 2023;72:593–619.