Invited Paper

Embracing uncertainties in computational imaging

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ABSTRACT

Modern computational imaging systems extend beyond conventional hardware constraints through advanced algorithms, yet they must inevitably contend with uncertainties at multiple levels, including imperfections in optics, sensor variability, model mismatch, environmental drift, and human or computational factors. This paper examines strategies for managing and leveraging such uncertainties within differentiable imaging frameworks. We show how uncertainty-aware design improves reconstruction robustness, noise tolerance, and adaptability. Rather than treating uncertainty as a hindrance, we argue that it can serve as a catalyst for algorithmic innovation, enabling imaging technologies that are more reliable, versatile, and effective in real-world environments.

Keywords: Uncertainty, Differentiable Imaging, Computational Imaging

1. INTRODUCTION

Uncertainty is intrinsic to all imaging systems. It arises from hardware misalignments, sensor limitations, model simplifications, environmental drift, and even human and computational errors. If unmodeled, these factors lead to discrepancies between physical measurements and computational reconstructions, undermining accuracy and reliability. Computational imaging has greatly expanded the capabilities of optical systems, but its sensitivity to mismatch underscores the need for frameworks that do more than suppress variability.

This paper follows the taxonomy illustrated in Fig. 1 to examine how uncertainties manifest in computational imaging and how differentiable approaches can incorporate them. By embedding these factors into the forward model, uncertainties become estimable variables rather than disruptive artifacts, transforming them from barriers into resources for system resilience.

2. DOMAINS OF UNCERTAINTY IN COMPUTATIONAL IMAGING

Uncertainty in computational imaging can be systematically categorized into several domains, each reflecting distinct physical or operational origins. While the manifestation of uncertainty is diverse, these domains provide a structured framework for analysis and mitigation.

Light and Optical Elements Imperfections in optical systems are a primary source of systematic uncertainty. Misalignment of optical components, aberrations introduced by imperfect lenses, and non-idealities in light sources collectively alter the forward model of image formation. Although these effects are often deterministic, they may also interact with stochastic variations such as source instability. Explicit incorporation of these factors into differentiable models enables joint optimization of both optical parameters and scene reconstruction, thereby reducing susceptibility to alignment errors and manufacturing tolerances.

Sensors Sensors introduce a combination of random and systematic uncertainties. Limitations in dynamic range may lead to clipping or loss of detail, while discretization introduces aliasing and quantization errors. Sensor noise, including thermal and electronic noise, adds a stochastic component, whereas calibration drift introduces bias over time. Accounting for these limitations within an uncertainty-aware reconstruction framework allows imaging algorithms to maintain robustness even when data acquisition is degraded or unstable.

Modeling and Calibration Epistemic uncertainties arise from the approximations and simplifications inherent in physical models. Linearization errors, incomplete descriptions of light–matter interaction, and unmodeled

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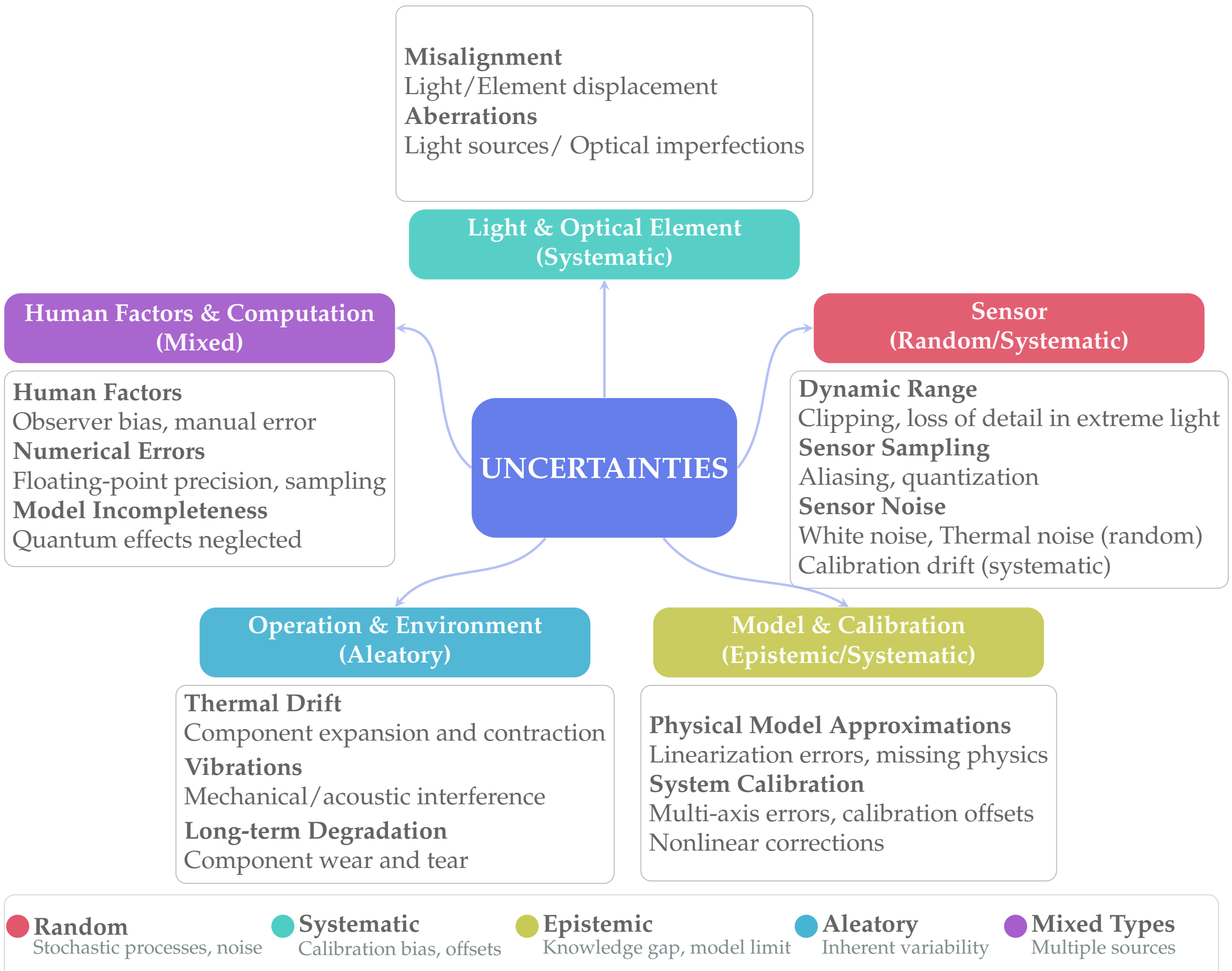

Figure 1. Representative sources and types of uncertainty in computational imaging. Categories span optics, sensors, modeling, environment, and human or computational factors. Types include random, systematic, epistemic, aleatory, and mixed forms.

scattering phenomena are common examples. Calibration processes also contribute systematic biases, particularly when multi-axis misalignments or offsets are present. Differentiable imaging provides a principled approach to embedding these uncertainties into the reconstruction process, aligning computational predictions more closely with physical measurements.

Operation and Environment Aleatory uncertainties stem from inherently variable operating conditions. Thermal fluctuations, mechanical vibrations, and long-term component degradation alter system behavior in ways that cannot be entirely eliminated. By incorporating such variability into forward models, differentiable frameworks allow imaging systems to adapt to changing environments, extending their reliability beyond controlled laboratory conditions.

Human and Computational Factors Finally, uncertainties also arise from human involvement and computational processes. Manual alignment, observer bias, and procedural errors can introduce systematic or random variability. At the algorithmic level, limitations in numerical precision and incomplete modeling of higher-order effects represent additional sources of error. These mixed uncertainties highlight the importance of designing reconstruction pipelines that are resilient not only to physical imperfections but also to procedural and computational constraints.

3. DIFFERENTIABLE FRAMEWORKS IN PRACTICE

The utility of this taxonomy is reflected across multiple computational imaging modalities. In holography, variations in defocus and illumination can be explicitly incorporated as variables within the forward model, enabling robust single-shot reconstructions under diverse experimental conditions.[1,2] Lensless imaging demonstrates similar benefits, where an end-to-end differentiable formulation that unifies super-resolution, autofocusing, and field recovery enhances resilience against sensor noise and calibration drift.[3]

Volumetric particle velocimetry further illustrates the value of uncertainty-aware modeling. By embedding multiple scattering phenomena into differentiable wave models, epistemic uncertainties in complex light–matter interactions are addressed directly, allowing reconstructions at particle densities that exceed the limits of conventional approaches.[4] Fourier ptychography provides perhaps the most comprehensive example, as aberrations, misalignment, and data degradation can be jointly optimized, thereby reducing dependence on pre-calibration procedures and enabling reliable operation in challenging environments.[5,6]

Taken together, these case studies demonstrate that by embedding diverse forms of uncertainty—random, systematic, epistemic, and aleatory—into differentiable models, computational imaging attains a level of robustness and adaptability that traditional methods are unable to match.[7,8]

4. CONCLUSION

Embracing uncertainty provides a foundation for resilient computational imaging. By integrating imperfections in optics, sensors, models, environments, and human or computational processes into differentiable frameworks, physics and computing can be bridged together,[9] and reconstructions become more accurate, stable, and adaptable to real-world variability.

Future research should further integrate uncertainty quantification with advanced learning architectures, explore real-time implementation under dynamic conditions, and extend these principles to other physical systems where the simulation–reality gap is critical. Similar challenges are evident, for example, in physical neural networks,[10] where the philosophy of uncertainty-aware differentiable modeling may prove equally valuable.

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