

End-to-end Metaoptic Inverse Design for Computational Imaging

Zin Lin⁽¹⁾

(1) Virginia Polytechnic Institute and State University, Blacksburg, VA 24061, USA,
zinlin@vt.edu

Metaoptic inverse design enhances spatial, spectral and polarization sensitivities by leveraging full-wave Maxwell physics—metaoptic interactions largely ignored by refractive or diffractive optics. Computational imaging transcends conventional optics by algorithmic reconstruction of high-fidelity information from limited optical measurements. We integrate metaoptic inverse design and computational imaging into a holistic end-to-end framework: a single-piece metaoptic frontend is optimized in conjunction with an image-processing backend to minimize reconstruction errors. The optics and computation are tightly coupled because the gradient of the backend error is propagated through the entire pipeline to the physical parameters of the frontend metaoptic. In contrast to optics-only or computation-only designs, the functionality or the operating principles of the frontend optics is not prescribed *a priori* but *spontaneously* emerges during the end-to-end optimization. Unfettered by human intervention, end-to-end discovery reveals nano-structures with enhanced data-acquisition capabilities and ultra-compact form factors.

A general formulation of our end-to-end framework is described below:

$$\min_{\epsilon, \alpha} L(\tilde{u}, u) \equiv \langle ||\mathbf{u} - \tilde{\mathbf{u}}||^2 \rangle_{u, \eta} \quad (1a)$$

$$\tilde{u} = \operatorname{argmin}_{\mu} ||G\mu - v||^2 + R(\mu; \alpha) \quad (1b)$$

$$v = Gu + \eta, \quad G \sim |E(r_{CCD}, \lambda)|^2 \quad (1c)$$

$$\nabla \times \nabla \times E(r) - \omega^2 \epsilon(r) E(r) = i\omega \delta(r - r_{OS}) \hat{p}, \quad (1d)$$

$$\omega = \frac{2\pi}{\lambda}, \quad \hat{p} \in \{\hat{x}, \hat{y}, \hat{z}\} \quad (1e)$$

Here, the loss function L is given by the averaged reconstruction error over several training objects u and noise realizations η . For each u , the estimate $\tilde{u}$ is obtained by solving a *nested* minimization problem (commonly known as the inverse scattering problem in computational imaging); the latter seeks to recover u from a raw image v (for example, noise-corrupted readings from a CCD sensor) by minimizing the data-fitting term $||G\mu - v||^2$ and an additional regularization function R . The measurement matrix G embodies the imaging optics and can be computed from the electric field intensities $|E|^2$ on the CCD sensor in response to a point dipole $\delta(r - r_O) \hat{p}$ at each position within the object space (OS). In our image-formation models, G can vary from convolutional kernels to full dense matrices. In fact, the richness and complexities of G that arise from the underlying Maxwell equation differentiate our framework from traditional refractive or diffractive optics. In particular, accurate computations of G require detailed simulations of the permittivity $\epsilon(r)$ as well as the gradient $\nabla_{\epsilon} G$ using the full Maxwell equation and its adjoint, taking into account strong spatio-spectral and polarization dispersions. We present several examples to illustrate the capabilities of our framework.