

# OPTO-ELECTRONIC CONVOLUTIONAL NEURAL NETWORK DESIGN VIA DIRECT KERNEL OPTIMIZATION

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## ABSTRACT

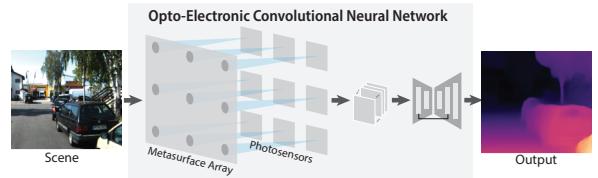
Opto-electronic neural networks integrate optical front-ends with electronic back-ends to enable fast and energy-efficient vision. However, conventional end-to-end optimization of both the optical and electronic modules is limited by costly simulations and large parameter spaces. We introduce a two-stage strategy for designing opto-electronic convolutional neural networks (CNNs): first, train a standard electronic CNN, then realize the optical front-end—implemented as a metasurface array—through direct kernel optimization of its first convolutional layer. This approach reduces computational and memory demands by hundreds of times and improves training stability compared to end-to-end optimization. On monocular depth estimation, the proposed two-stage design achieves twice the accuracy of end-to-end training under the same training time and resource constraints.

**Index Terms**— Opto-electronic neural networks, metasurfaces, depth estimation

## 1. INTRODUCTION

Opto-electronic neural networks integrate optical front-ends—such as transmission masks [1], diffractive optical elements [2], and metasurfaces [3]—with electronic back-ends based on conventional neural architectures to perform vision and imaging tasks. By leveraging optics to preprocess signals before electronic inference, such systems offer the potential for low-latency [4] and energy-efficient [1] computation. However, most existing approaches rely on an end-to-end training paradigm in which both the optical components and the electronic layers are optimized jointly [2, 3, 4, 5, 6]. In practice, this end-to-end scheme requires excessive computational resources as the optical simulators are expensive to evaluate and the search space has a much higher dimension than purely optimizing computational models [6].

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**Fig. 1:** We consider an opto-electronic convolutional neural network (CNN) that integrates a metasurface array with an electronic backend. The metasurface, a flat nanophotonic device, encodes the incident light from a scene into optical feature maps. As light propagates through the metasurface, it undergoes a phase modulation equivalent to convolving the common photograph of the scene with an engineered kernel. These optically generated feature maps are then processed electronically by a conventional CNN architecture.

In this work, we propose an alternative strategy for designing opto-electronic *convolutional* neural networks (CNNs) that alleviates the challenges of end-to-end training. Instead of optimizing the hybrid system jointly, we first train a conventional electronic CNN (or employ a pre-trained model) and then design the optical front-end—implemented as a metasurface array—to replicate its first convolutional layer through *direct kernel optimization* (DKO). Compared to end-to-end optimization, this two-stage approach substantially simplifies the design process: the dimension of the variables to be optimized simultaneously is greatly reduced.

We demonstrate these advantages by designing and simulating opto-electronic CNNs for an exemplar task: monocular depth estimation. According to our analysis, the proposed two-stage method achieves two-fold higher accuracy than the end-to-end scheme under identical hardware and training-time constraints. Furthermore, the dimension of the parameter space and computational cost of end-to-end training are hundreds of times higher, whereas the proposed approach maintains a significantly smaller computational footprint. In summary, the key contributions of this paper are:

- A two-stage strategy to design opto-electronic CNNs for vision and imaging;

- An exemplar opto-electronic CNN designed using the two-stage strategy for monocular depth estimation;
- A comprehensive simulation study that demonstrates the accuracy, efficiency, and stability benefits of the proposed two-stage strategy over traditional end-to-end optimization.

## 2. RELATED WORK

Incorporating optics into artificial vision and imaging systems has emerged as a vibrant discipline, fueled by recent advances in optical fabrication technologies that now enable the accessibility of custom devices such as diffractive optical elements [7] and metasurfaces [8]. Collectively referred to as computational optics, these devices form feature maps—rather than conventional photographs—on the photosensor. Such feature maps can be understood as scene embeddings, generated according to engineered sensitivities of the optical devices [9, 10].

Based on their functionalities, these systems can be broadly divided into two categories. The first category exploits the optics’ intrinsic sensitivity to scene properties—such as depth [5, 11, 12], spectrum [3, 13], and polarization [14, 15]—to encode this information into the feature map through point spread functions (PSFs) that vary with the underlying scene attributes. The second category seeks to emulate part [6, 3, 16] or all [4, 17] of a deep neural network architecture in the optical domain. Platforms in this class harness optics’ inherent speed and parallelism, employing one or more layers of optical arrays in which each element performs a linear transformation, such as a convolution, on the output of the preceding layer. Such fully or partially optical neural networks have been experimentally demonstrated on basic vision tasks, including image classification [3, 18, 19].

These computational optics systems are often designed in an end-to-end (E2E) manner, where the optical elements and computational parameters are jointly optimized under a unified loss. Such co-optimization has been shown to yield superior local optima compared to separately designing the optics and the computation [5, 2]. Nonetheless, implementing end-to-end optimization is challenging: the optical module requires differentiable solvers for light propagation—whether wave-based [20, 21, 22], ray-based [23, 24, 25], or hybrid approaches [26]—all of which are computationally intensive and significantly enlarge the design search space.

## 3. SYSTEM DESIGN

The proposed opto-electronic CNN, illustrated in Fig. 1, employs a 2D metasurface array to simultaneously encode the scene into  $M \times N$ -channel optical feature maps on a shared photosensor. This metasurface layer functions as an optical approximation of the first convolutional layer of a pre-trained

CNN. The resulting features are then fed into the subsequent electronic layers of the CNN, which process the features to generate the final output.

### 3.1. Optical Model

Consider an incoherent scene located at a distance much larger than the spatial extent of the metasurface array. The incident environmental light can be modeled as a superposition of incoherent plane waves with amplitude distribution  $J(\mathbf{k})$  as a function of the wave vector  $\mathbf{k} = [k_x, k_y, k_z]$ . Each planar wavefront right before the metasurface is expressed as:

$$U(x, y; \mathbf{k}) \approx A_0(\mathbf{k}) \exp[j(k_x x + k_y y)], \quad (1)$$

where  $(x, y)$  denotes the coordinates on the metasurface array, and  $A_0(\mathbf{k})$  is the amplitude of the plane wave.

Each metasurface element  $(m, n)$  is characterized by a modulation profile  $C_{m,n}(x, y)$ , which can be written as

$$C_{m,n}(x, y) = T_{m,n}(x, y) \exp[j\varphi_{m,n}(x, y)], \quad (2)$$

with  $T_{m,n}(x, y)$  and  $\varphi_{m,n}(x, y)$  representing the amplitude and phase modulation, respectively.

The resulting power distribution generated by metasurface  $(m, n)$  under an incident plane wave  $\mathbf{k}$  is determined by free-space propagation of the modulated wavefront [27]:

$$P_{m,n}(u, v; \mathbf{k}) \propto A_0^2(\mathbf{k}) \left| \tilde{C}_{m,n} \left( \frac{u - k_x s}{\lambda s}, \frac{v - k_y s}{\lambda s} \right) \right|^2, \quad (3)$$

where  $\tilde{C}_{m,n}$  denotes the Fresnel diffraction pattern of the modulated wavefront produced when a front-parallel plane wave propagates through the metasurface  $C_{m,n}$  [20]. Eq. 3 indicates that the measurement formed on the photosensor,  $I_{m,n}$ , is a convolution of the pinhole image of the scene with an engineered kernel determined by the metasurface:

$$I_{m,n}(u, v) = \int_{\mathbf{k}} P_{m,n}(u, v; \mathbf{k}) d\mathbf{k} \\ = I(u, v) * h_{m,n}(u, v),$$

$$\text{where } I(u, v) = \int_{\mathbf{k}} A_0^2(\mathbf{k}) d\mathbf{k} \quad (\text{pinhole image}), \quad (4)$$

$$h_{m,n}(u, v) = \left| \tilde{C}_{m,n} \left( \frac{u}{\lambda s}, \frac{v}{\lambda s} \right) \right|^2 \quad (\text{kernel}).$$

This property enables using metasurfaces to perform convolutional operations with desired kernel  $h_{m,n}$  by designing the modulation profiles  $C_{m,n}$  [3, 14].

For convolutional kernels  $h_{m,n}$  that contain negative values, we design two metasurfaces with modulation profiles  $C_{m,n,+}$  and  $C_{m,n,-}$ , and approximate the kernel response by subtracting the two corresponding measurements. In addition, because metasurfaces are generally dispersive, the effective kernels vary with wavelength and are only partially

correlated across the spectrum. To simplify the analysis, we restrict each metasurface to operate at a single wavelength of incident light. This can be practically achieved by placing a narrow bandpass filter in front of each metasurface.

To extend the design to CNNs that process RGB images, where each kernel  $h_{m,n}$  consists of three channels, we construct three independent pairs of metasurfaces  $C_{m,n,\pm,R}$ ,  $C_{m,n,\pm,G}$ , and  $C_{m,n,\pm,B}$ . Each pair transmits only a narrow spectral band (red, green, or blue) from the scene and is assumed to implement a kernel that remains constant within that band. Consequently, to approximate the first convolutional layer with  $L$  output channels for RGB inputs, the metasurface array requires  $6L$  elements.

### 3.2. Direct Kernel Optimization

We optimize a pair of metasurface phase modulation profiles,  $\varphi_{m,n,+}(x, y)$  and  $\varphi_{m,n,-}(x, y)$ , assuming uniform transmittance profiles  $T_{m,n,\pm}(x, y)$  within a predefined circular aperture, to approximate a given single-channel target kernel  $h_{m,n}$ . The optimization is formulated as

$$\arg \min_{\varphi_{m,n,\pm}(x, y)} \|\text{Simulator}(\varphi_{m,n,+}(x, y)) - h_{m,n,\pm}(u, v)\|^2, \quad (5)$$

where

$$h_{m,n,\pm}(u, v) = \frac{\pm h_{m,n}(u, v) + |\pm h_{m,n}(u, v)|}{2}.$$

We adopted the D-Flat differentiable simulator to generate the kernel given the phase modulation profiles [20]. After determining the optimal phase modulation,  $\varphi_{m,n,\pm}(x, y)$ , we translate them into a metasurface geometries by performing a standard cell-based library search [28].

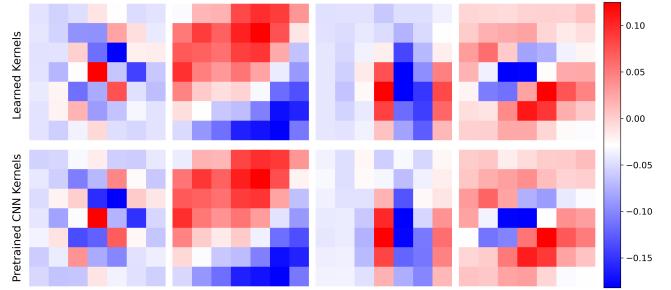
## 4. RESULTS AND ANALYSIS

In this paper, we focus on analyzing the proposed two-step strategy for designing opto-electronic CNNs and compare it with the traditional end-to-end strategy in simulation. The accuracy of the employed simulation process has been validated in our prior work [20], which showed that the simulated kernels closely matched those measured from fabricated metasurfaces designed with the same framework [14].

To facilitate analysis, we select monocular depth estimation as the target application for our study, and design the opto-electronic CNN based on a pre-defined architecture, Monodepth2 [29]. This architecture takes a single RGB image as input, and its first convolutional layer contains 64 channels. Consequently, a total of  $384 = 64 \times 6$  metasurfaces need to be optimized to carry out the first layer operation optically. For each metasurface  $(m, n)$ , the phase modulation profile  $\varphi_{m,n}$  is parameterized as a  $1025 \times 1025$  discrete 2D matrix with a pixel pitch of  $2.5 \mu\text{m} \times 2.5 \mu\text{m}$ . The spacing between the metasurface array and the photosensor, i.e., the

Method	Parameters (M)	Time (ms)
DKO	1.1	100
Computational Training	14.84	250
E2E	418	73,000

**Table 1:** The number of trainable parameters (in millions), and the computational time (in milliseconds) for one forward pass and backward propagation for our DKO method (first row), the computational training of Monodepth2 (second row), and the E2E method (third row).



**Fig. 2: Top row:** Sample metasurface-learned kernels  $h_{m,n}(u, v)$ , and **bottom row:** corresponding kernels from the pretrained Monodepth2 model. Our optimized metasurfaces learn PSFs that closely match the original model’s kernels.

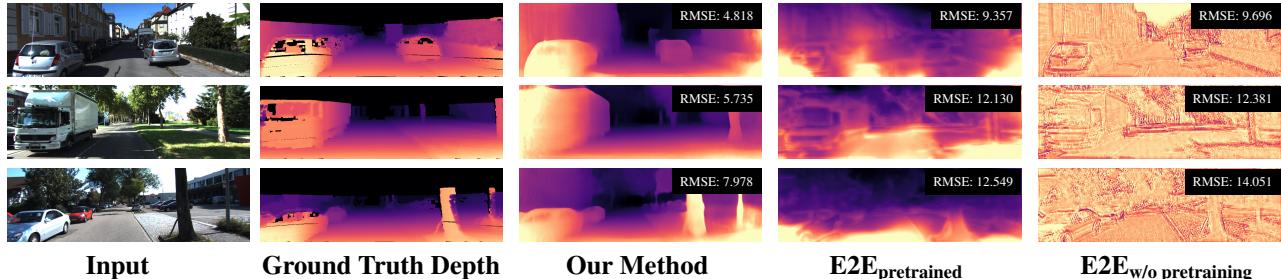
sensor distance, is set to 10 mm. The resolution of the feature maps generated by each metasurface is  $320 \times 96$ . We adopt the KITTI dataset [30] for training, evaluation, and testing.

**Computational cost of training.** Under our parameter settings, the optical layer contains 403M trainable parameters. By comparison, the first convolutional layer implemented electronically would require only 9k parameters, and the entire Monodepth2 architecture has just 14M parameters in total. Thus, an end-to-end training strategy would necessitate optimizing more than 400M parameters jointly. In contrast, the proposed two-step strategy decouples the optimization of the optical layer from that of the electronic layers, and further breaks down the optical optimization into independent metasurface-level subproblems, substantially reducing the dimensionality of the search space (Table 1.)

Moreover, end-to-end optimization requires rendering the full feature map of the scene using variants of Eq. 3, whereas our two-step approach only evaluates the kernels (Eq. 5) with-

NCC↑	RMSE↓	MAE↓
0.9840	0.012909	0.007555

**Table 2:** Average normalized cross correlation (NCC), root mean square error (RMSE), and mean absolute error (MAE) for all  $64 \times 6$  kernels produced by our optimized metasurface against the ground truth Monodepth2 first layer kernels.



**Fig. 3:** Qualitative comparison on the KITTI dataset (simulation). The first column shows the input image; the second column shows the sparse ground-truth depth map; the third column shows the result from a simulated opto-electronic CNN, where the first convolutional layer is implemented by a metasurface and trained using the proposed two-stage strategy; the fourth and fifth columns show results from the same system trained end-to-end, initialized with and without the pretrained model, respectively. All design strategies utilize uniform training time (12h) and computational resources (one A100 GPU). The proposed two-stage strategy shows significantly better visual quality and accuracy compared to E2E strategies. The inset numbers indicate the RMSE (in meters) for each prediction.

Experiment	AbsRel	SqRel	RMSE (meters)	RMS <sub>log</sub>	$\delta < 1.25$	$\delta < 1.25^2$	$\delta < 1.25^3$	Time
Ours	<b>0.199</b>	<b>1.674</b>	<b>6.996</b>	<b>0.305</b>	<b>0.688</b>	<b>0.879</b>	<b>0.944</b>	12h
E2E <sub>pretrained</sub>	0.346	3.618	11.013	0.494	0.401	0.675	0.835	12h
E2E <sub>w/o pretraining</sub>	0.443	4.758	12.083	0.587	0.303	0.561	0.766	12h

**Table 3:** Quantitative comparison on the KITTI dataset (simulation). Our two-stage strategy clearly achieves better performance than the E2E strategies under uniform training time and resources.

out the rendering step. This greatly reduces the computational burden during backpropagation. The computational advantages of the proposed two-step strategy are shown in Table 1.

**Direct kernel optimization.** Our DKO approach effectively generates metasurfaces whose kernels closely match the target ones. As shown in Fig. 2, the learned kernels align well with the Monodepth2 target kernels, indicating that our metasurfaces would produce feature maps highly consistent with those of the original model. Note that the visualized kernels represent the final form, with negative components already subtracted from the positive ones. Table 2 reports quantitative evaluations across all learned kernels, further validating this close correspondence.

**Depth estimation.** We trained the Monodepth2 architecture from scratch and optimized the metasurface kernels to match those in its first convolutional layer. The entire process completed in under 12 hours on a single Nvidia A100 GPU. In contrast, the E2E approach failed to produce meaningful results within the same time and computational budget, owing to its prohibitive resource demands—even when the computational module was initialized to the pretrained model. Qualitative and quantitative comparisons between our strategy and the E2E baseline are shown in Fig. 3 and Table 3, respectively. The E2E optimization must jointly tune hundreds of millions of optical parameters, requiring repeated convolutions and backpropagation through the optical module for ev-

ery batch. Based on our projection, achieving convergence via the E2E method would take approximately  $60\times$  longer under the same computational conditions.

## 5. CONCLUSION

We proposed a two-stage framework to address the high computational cost of end-to-end training in hybrid opto-electronic CNNs. The method first trains a purely computational CNN, then directly optimizes a metasurface to reproduce the kernels of its first convolutional layer, effectively replacing that layer with an optical counterpart.

Unlike prior approaches that focused on tasks with low-dimensional outputs, such as object or digit classification, our simulation shows that DKO enables efficient design of hybrid systems for dense prediction problems like depth estimation, which require spatially resolved outputs. By decoupling and dividing optical optimization from full end-to-end backpropagation, DKO achieves substantial reductions in training time and computational cost while preserving the accuracy of the pure computational network.

The framework extends naturally to other dense-prediction tasks—such as semantic segmentation and surface normal estimation—and provides a practical pathway toward scalable hybrid vision systems that more fully leverage the strengths of optical computing.

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