2D Beam Shaping via 1D Spatial Light Modulation and Meta-optics

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Abstract: A metasurface system is proposed to perform a non-trivial 1D-to-2D optical transform. Gradient based methods for a metasurface doublet are used to optimize input-output relation yielding an effective 2D SLM from a 1D SLM. © 2021 The Author(s)

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Fast, dynamic manipulation of two-dimensional (2D) optical fields is integral to emerging applications like optical holography, non-line-of-sight imaging [1], optical neural network [2] and imaging through disorder. Currently most of these application use either digital micromirror devices (DMD) or liquid-crystal based spatial light modulators (SLM). Both existing technologies suffer from low-speed operation. Several phase-shifter technologies, such as, electro-optic modulation via free carrier dispersion [3] or Pockels effect [4] can potentially increase the speed by several orders of magnitude. An attractive solution will be to map a 1D array of $N^2$ phase-shifters to a 2D array of $N \times N$ pixels, which can perform the 2D optical wave-front modulation without difficulty in routing the electrical control signals. In fact, a recent work [5] used a random medium to enable a similar functionality for imaging through disordered medium, although an arbitrary wavefront shaping as needed for a 2D SLM was not demonstrated.

We propose a method to create an arbitrary 2D wavefront by controlling the pixels arranged in a 1D array. The key is an inverse-designed multi-layer meta-optical structure that maps an input point source located at different angles to a spatial function, that forms an orthogonal 2D basis. We optimize a 1D-to-2D transform that maps pixels from a 1D SLM to an effective 2D SLM. Figure 1 shows the proposed optical architecture for the 1D to 2D SLM. The laser light is modulated using a 1D array of tunable pixels which is passed through a composite meta-optics. These two meta-optics are designed to take the light from each pixel to create a 2D field distribution at a specific plane.

The forward model simulates the light propagation from a 1D SLM through free space and includes the light’s interaction with discretized phase masks, that can be implemented using metasurfaces [6]. We note that, while modelling a metasurface as a phase-mask is an approximation, it largely holds true for many different devices, as shown by many research groups [2, 9, 10].

We employ band-limited angular spectrum method to simulate the forward propagation to reduce simulation memory requirements [7]. In our model, the electromagnetic (EM) wave is treated as a monochromatic scalar wave when traveling through the phase masks and free space the light with a wavelength $\lambda$ from the input source $E(x,y)$ is propagataed through a distance of $d$ in the free space:

$$E(x,y,z_0) = E(x,y,0) * h(x,y,z_0)$$

$$\mathcal{F}\{h(x,y,z_0)\} = e^{j2\pi xz_0\frac{1-(Mx)^2-(My)^2}{\lambda}} \times \text{filter}(f_x,f_y)$$

$E(x,y,z)$ is the electric phasor field, $h(x,y,z)$ is the angular spectrum convolution kernel, and $\mathcal{F}$ is the 2D spatial Fourier transform operator, and $z_0$ is the propagation distance. The filter($f_x,f_y$) function is a mask that limits the spatial bandwidth to be lower than $f_x$ and $f_y$ [6].

This forward model is then used in a machine learning framework to design the metasurfaces to perform the 1D-to-2D mapping. A cost function is constructed based on a desired input-output mapping:

$$C = -\prod_k \left( \sum_{i,j} \gamma_k^{(i)} \gamma_k^{(j)} \right)$$

where $\gamma_k$ and $\tilde{\gamma}_k$ are the target and the output spatial distribution, respectively for the $k^{th}$ input mode (in this case each pixel in the 1D array). $N$ is the number of pixels in the 1D array. $i$ and $j$ are the indices of the field matrix. This cost function is designed to make the output modes similar to the desired modes while ensuring that each output mode contains similar power. The phase masks are optimized using a gradient descent algorithm facilitated by the graph based linear algebra library TensorFlow [11]. The phases are updated using the ADAM optimizer implementation in TensorFlow. Finally, individual optical scatterers are mapped to best approximate the phase profiles yielding...
functional meta-optical structures. Elements composed of subwavelength scatterers with arbitrary phase transmission properties are generated.

Using these phase masks, we map a 1D array to a 2D field distribution. When excited by individual pixels from the 1D SLM, the output field at the 2D SLM output will illuminate. The output fields are well defined within the output pixel boundary. Figure 2a shows the 1D array of 49 dots. Each dot maps to a specific point in the 2D plane (shown in the 7 × 7 array in Figure 2b) when passing through two phase-masks.

![Figure 1. Proposed optical architecture for 1D-to-2D mode converter. Coherent light is focused into a line to efficiently illuminate a linear array of 1D SLM pixels. Light is reflected into the pair of meta-optical structures and into the camera, creating arbitrary 2D patterns.](image)

![Figure 2. a) Input 49 element 1D SLM with all input pixels illuminated b) Set output modes for 1D 49 element SLM input](image)

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