Supplementary Information: Learning incoherent light emission steering from metasurfaces using generative models

1. Experimental Details

1.1. Design principles of the metasurface

Dielectric metasurfaces are made up of a sub-wavelength array of optical nano-resonators which can exert complete control over the phase, amplitude and polarization of light. Here we design a reconfigurable metasurface that can dynamically control the direction of light emission from within the metasurface. This design process is done using a commercial electromagnetic wave simulator - Lumerical FDTD - which solves Maxwell's equations in the time-domain, and Fourier transforms the solution to gain information about the optical resonators based on the refractive index distribution. The reflection properties of a single unit-cell (nano-pillar) of GaAs resonators sitting on a distributed Bragg reflector (DBR) stack are calculated using the 'grating s-params' module in Lumerical FDTD at the emission wavelength of the InAs quantum dots (QDs). We model the semiconductor alloy composition, refractive index distribution, the geometry (height, width, pitch etc.) of the resonator and DBR as optimization parameters. The properties of reflection (amplitude and phase) of this metasurface are used as the figure of merit to optimize for these geometries and refractive indices. Ideally a reconfigurable metasurface, we want to maximize the phase shift as a function of the absorbed pump intensity while minimizing the optical absorption losses due to the free-carrier generation. These metasurface are typically made up low quality factor ($Q_f \simeq 25$) resonances which by design can change the phase of light near the resonances by nearly 2π with minimal absorption losses in the resonator. As the optical pump photons are absorbed by the GaAs resonators, we create populations of electrons and holes for a very short (carrier lifetime of 2-6ps [1, 2]) period of time with in the GaAs resonator. During this time period - the refractive index of the resonators get modified based on the Drude free-carrier effect such that more carriers decreases the real part and increases the imaginary part of the index. We specifically chose GaAs as the resonator material due to its low-electron effective mass leading to large index change with minimal pump intensity. This change in the refractive index as a blue shift in the resonant wavelength while increasing the absorption of the same. Thus as the resonance blue shifts through the emission wavelength of the metasurface (1250nm), the phase of the light reflected form the metasurface shifts. The optical pump profile from the spatial light modulator (SLM) which translates into a refractive profile induces a spatial phase profile on the metasurface which ultimately forms the additional optical momentum steering the emission from the embedded InAs QDs.

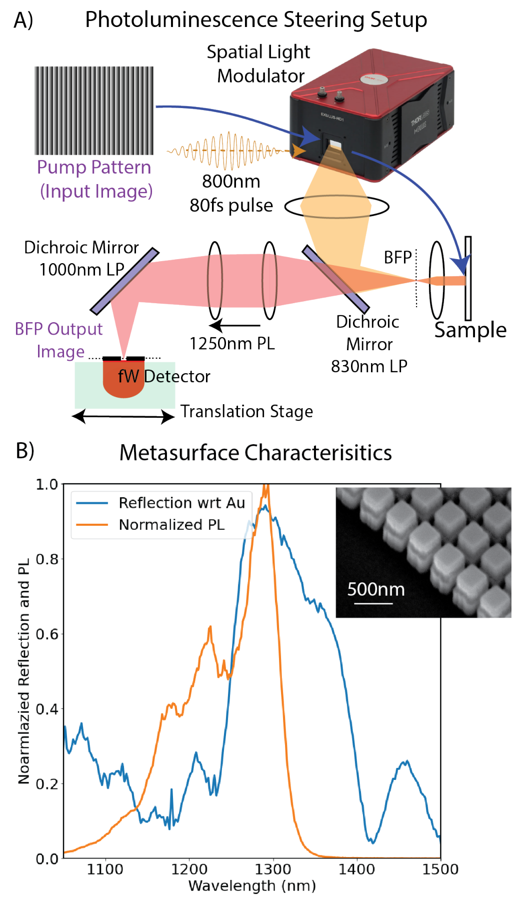

Figure 1. **Experimental Details**: A) Measurement setup for PL steering. The schematic shows how the optical pump pattern on the 800nm pulse is imaged onto the sample using the spatial light modulator (SLM). The PL from the sample is imaged in the back-focal-plane (BFP) of the objective lens to form the output of the system. The blue arrows indicate propagation of the input image from the SLM to be de-magnified and projected on to the metasurface sample. B) Metasurface Characteristics: Reflection (blue curve) of the metasurface with respect to gold and emission spectra (orange curve) from the metasurface during continuous wave pumping at 808nm. The peak in reflection coincides with the peak in emission from the metasurface. The inset at the top of the graph shows an SEM image of the fabricated metasurface

1.2. Growth and fabrication of the semiconductor metasurface

The semiconductor metasurface layers are grown using molecular beam epitaxy. The GaAs substrate is degassed prior to growth at 630°C for 10min under an As overpressure. The 15 DBR layers of AlAs (index = 2.92) and $Al_{0.3}Ga_{0.7}As$ (index = 3.2) was grown on this substrate. The GaAs (index = 3.35-3.50, based on the optical pump intensity) resonator of 670 nm height with embedded 5 layers of InAs quantum dots grown inside $In_{0.15}Ga_{0.85}As$ quantum wells was grown at 490°C. A pyrometer was used to continuously monitor the temperature during the growth and a reflected high energy electron diffraction beam pattern was used to confirm the formation of the quantum dots. These epitaxial thin films were used to fabricate the metasurface resonators using electron-beam lithography with PMMA to lift-off an alumina hard-mask and a dry (Cl_2) etching procedure. See Fig 1B inset for the scanning eletron microscope (SEM) image of the metasurface at the nano-scale.

1.3. Measurement Setup

The photoluminescence (PL) steering from the metasurface was measured as function of the applied grating order on the SLM at different emission angles by translating a point detector in the image of the back-focal plane of the main objective (See Fig S1A). We used a femto-Watt InGaAs detector with lock-in amplifier while chopping the pump beam. We used the Astrella Ti-Sapphire laser source at 800 nm with 1 KHz repetition rate with 80fs pulse width to pump the metasurface with 2-3 mJ/cm^2 energy density. We used the Thorlabs Exulus-4K SLM which operates at refresh rate of 60 Hz with 3840 X 2160 pixels. The reflection spectra was measured using a Halgoen lamp white light source and near infrared Ocean Optics spectrometer. The dark noise of the spectrometer was substrate and the spectra was normalized to the reflection from a gold substrate. The PL spectra in Fig S1B was measured by pumping the metasurface using continuous wave 808 pump at 1 mW and 100 ms integration time of the same spectrometer.

2. Variational Autoencoder training details

The training set for our VAE [3] consisted of 1D profiles generated using periodic Bezier curves, which represent periodic profiles with arbitrary linear as well as nonlinear variations within each period. To generate the training set, we randomly choose a periodicity between 48 and 3840 pixels. Within each period, we define a Bezier curve parametrically as follows:

$$B(t) = (1-t)^3 P_1 + 3(1-t)^2 t P_2 + 3(1-t) t^2 P_3 + t^3 P_4 \quad (1)$$

where P_1, P_2, P_3, and P_4 are the four points used to define the bezier curve, and t is a parameter between 0 and 1. In our case, we fix P_1 = (0, 0) and P_4 = (1, 1), and randomly generate two pairs of points P_2 and P_3 between P_1 and P_4.

We generate a database of 50,000 1D profiles, split into an 80-20 train-test set.

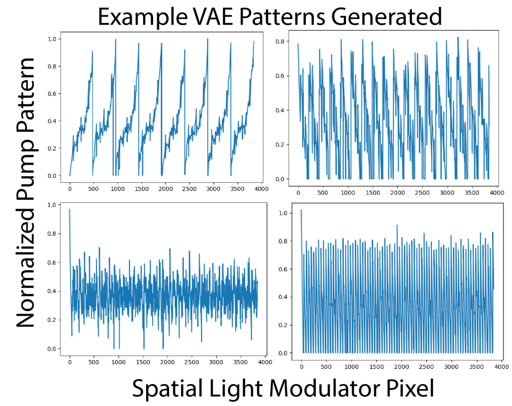

Figure 2. Panels show some example pump patterns generated by the VAE after training. We see a mixture of low frequency and high frequency pump patterns, as well as patterns with varying average intensity

The encoder consists of three standard feed-forward layers of a 1000, 1000, and 100 units each, while the decoder mirrors this architecture. Each layer uses a 'relu' activation function [4]. We use a mean squared error loss to quantify the reconstruction error, with the Kullback-Liebler divergence term defined in the conventional manner.

Using this database, we train the VAE with a latent dimension of 3 and using the Adam optimizer [5] with a learning rate of 0.001. Training is performed on a batch size of 32 for a 1000 epochs. Fig S3 shows sample 1D profiles generated by the VAE, and the associated input SLM image. We find these images to realize pump patterns beyond human intuition, and find that some of these patterns result in significant beam steering.

References

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