Inverse Design of Plasmonic Phase-Contrast Image Sensors Using Denoising Diffusion Probabilistic Model

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Abstract: We use a generative deep learning method based on denoising diffusion probabilistic model to improve the design of plasmonic phase-imaging sensors for broadband operation. This flexible method enables optimized inverse design for a wide range of target specifications.

1. Introduction

Generative deep learning techniques, such as generative adversarial network (GAN) and variational autoencoder (VAE), have recently emerged as a powerful tool for the design of nanophotonic devices with advanced operational characteristics [1, 2]. This approach is particularly well suited for the development of flat-optics metasurface devices, which typically involve a large number of geometrical parameters to be optimized. Substantial work has already been reported on the deep learning inverse design of metasurface-based free-space passive components such as metalenses [3]. The past few years have also seen an explosive increase in research on a novel generative deep learning method, called denoising diffusion probabilistic model (DDPM) [4], which has been applied to text-to-image generation services, including Dall·E and Stable Diffusion. Its first application to nanophotonics has only just been reported [5].

Here we consider active metasurface devices designed to interface free-space radiation with waveguided modes for wavefront sensing and phase imaging applications, following our recent work with plasmonic grating couplers [6]. Compared to conventional phase imaging systems [7] that require complex and bulky setups, these devices can measure the phase gradient of the incident light directly, without the need for additional optical elements. However, the diffractive devices of our prior work [6] are limited to operation under monochromatic illumination due to their strong spectral dispersion, which renders them unsuitable for practical scenarios involving broadband light. Achieving achromatic operation requires intricate metasurface structures, which are incompatible with trial-and-error design methodologies. In this work, we employ DDPM to design a wavefront sensing meta-structure with enhanced response and reduced spectral dispersion.

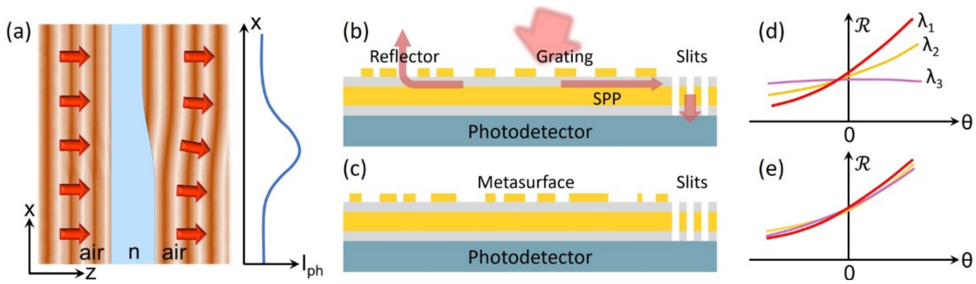

Fig. 1. (a) Light transmission through a phase object and its detection with angle-sensitive photodetectors. (b) Plasmonic angle-sensitive device based on a simple periodic grating [6]. (c) Similar device with an aperiodic nanostripe array optimized by machine learning. (d), (e) Responsivity $\mathcal{R}$ vs incidence angle θ at different wavelengths for the devices of (b) and (c), respectively.

2. Device design, results, and discussion

The transmission or reflection of light from a transparent phase object results in a deflection by an angle proportional to the local phase gradient [Fig. 1(a)]. Our devices consist of planar photodetectors coated with a plasmonic structure that introduces a sharp dependence of responsivity $\mathcal{R}$ on illumination angle θ around normal incidence. In our prior work [6], this structure was based on a metallic diffraction grating designed to couple light incident at a small angle from the surface normal to surface plasmon polaritons (SPPs) supported by an underlying metal film [Fig. 1(b)]. These guided waves are then scattered into the detector active layer by a set of slits perforated through the metal film on one side of the grating. On the other side, an aperiodic array of metallic nanostripes (reflector) is used to scatter any incoming SPPs back into free-space radiation. As a result, the photodetector responsivity exhibits a strong asymmetric dependence on angle of incidence [Fig. 1(d)], which allows measuring the local direction of light propagation. When combined in a pixel array with an imaging lens, these devices can therefore be used to sense the incident wavefront, and thus image transparent phase objects for applications such as biomedical microscopy and surface profiling [6].

In the present work, we employ a generative deep learning approach to design a fully aperiodic array of metallic nanostripes [Fig. 1(c)] that can replace the diffraction grating and reflector region of our previous devices, and correspondingly produce the desired asymmetric angular response with large slope over a broad spectral region [Fig. 1(e)]. In the design protocol, a 15-µm-wide grating region is represented by 1500 pixels, each with 10-nm width either with or without a Au nanostripe coating. A minimum feature size of 50 nm (consistent with state-of-the-art nanofabrication processes) is enforced during the training data generation and sampling processes. Initially, 1650 designs of random patterns and periodic gratings with different pitch, width, and chirp were created and modeled by Lumerical/Ansys FDTD simulations (where we computed the transmittance through the metasurface into the underlying photodetector active layer). Each design is represented by a 1D vector with 1500 elements plus 100 dummy elements for U-NET size constraint and is labeled with its transmittance data at two angles (+1 and -1 degrees) and multiple wavelengths (from 1500 to 1600 nm), which are used to train the DDPM network.

The training process consists of DDPM training with labels (classes) as shown in Fig. 2(a), wherein the denoising process uses a 1D U-NET, and 1000 time steps are chosen. The training time is typically 15 minutes for 500 epochs on a PC with an RTX 4090 GPU board. We then take the four best training data as the initial data x_S, with added noise, and after the denoising process we obtain the output grating data x_0. The generation (sampling) phase is depicted in Fig.2(b). For the injection of the initial data x_S, the time step of $S = 994$ is chosen to balance the resemblance to the input data and some randomness to generate better data. For the selection of the input data x_S, we use a figure of merit consisting of two components: the mean value and standard deviation of the slope of transmittance versus angle around normal incidence (i.e., the difference between transmittance at +1 deg and -1 deg) at different wavelengths. The sampling process of 64 grating data takes 15 seconds, and additional FDTD validation takes 30 seconds each. We iterate the training and generation process twice, with a total computational time of less than 2 hours.

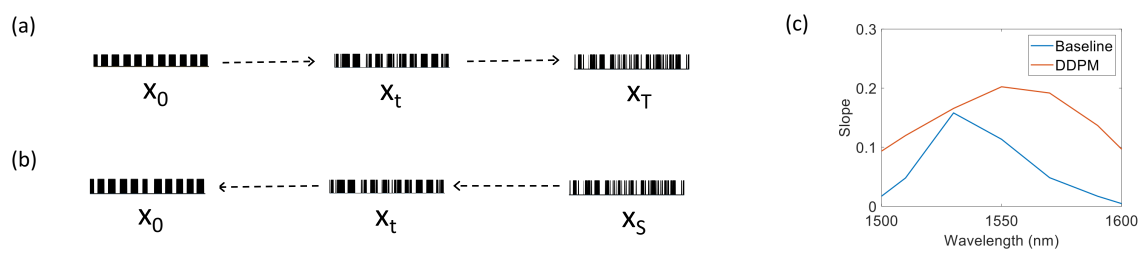

Fig. 2 (a) DDPM training process, wherein a 1D U-NET is used to describe the denoising process with additional labels, and T = 999 is used. (b) Sampling method, where known good grating patterns with noise are injected at time x_s, with s = 994 chosen in our case. (c) Slope of the angular response around normal incidence vs wavelength for the original baseline design [6] and for the optimized design generated by deep learning.

The slope data for the best design, optimized by deep learning for broadband high-slope angular response in the 1500 – 1600 nm spectral range, are shown in Fig. 2(c) together with those of the baseline design (the device of ref. 6). It is clearly seen that the deep learning design features a much higher slope across the entire wavelength range considered in these simulations compared to the baseline device. As a result, this new design would allow for accurate wavefront sensing and unambiguous phase imaging under broadband illumination across the same spectral range. The optimized Au metasurface pattern is aperiodic with uneven pitch, linewidth, and spacing of all the nanostripes, and thus would be impractical to design using a parameter sweep. Additional related nanophotonic applications and optimization methods for the DDPM-based inverse design process will also be presented.

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4. References

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