Multi-level Diffractive Lens and Metalens Optimization with Machine Learning

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Introduction

All existing materials carry information that can be processed by a data analysis. The field of material informatics (MI) integrates material science with data science to build technologies for better aiding scientists in various fields These technologies find materials with preferred properties, distinguish materials with optimal structures or composition, generate microstructures or nanostructures, and discover novel materials—such as materials for thermoelectric, lithium-ion batteries, and nitride semiconductors. [2] By assisting the experiment process, the duration and cost of the research and fabrication of the materials are significantly reduced.

One application of MI in photonics aims to develop different types of structures that manipulate light—such as a conventional convex lens. A conventional lens is a transparent material with at least one curved side to either concentrate light or disperse light. To concentrate light, a convex or refractive lens uses the phenomenon of refraction, where the bending of a wave occurs due to the changes in the speed of the wave as it travels into another medium (i.e., light wave traveling from air into glass) as shown in Figure 1(a). In the recent decade, many applications with refractive lenses—such as cameras, telescopes, and imaging—have been replaced with flat lenses due to its increased focusing efficiency. The focusing efficiency is the measure of the intensity of the light gathered at the point at which the light wave meets after exiting the lens. These flat lenses mimic the focusing of light that is achieved through a refractive lens without changes to thickness.

All flat lenses are designed and fabricated differently. A diffractive optical element (DOE) or diffractive lens focuses light waves by exploiting the phenomenon of diffraction, which occurs when the light wave passes across an edge that results in the bending of the wave as demonstrated in Figure 1(b). In photonics, a standard DOE is a multi-level diffractive lens (MDL). MDLs have spatially arranged sets of concentric circles on the substrate (i.e., glass wafer) known as the Fresnel Zone Plate (FZP) pattern. Each concentric circle has a blazed phase structure, which resembles stair-like structure shown in Figure 2(a). [4, 6] These structures ensure optimal bending of the light waves. Due to the simple design and accessibility of MDLs, these lenses are commonly found in applications like optical communications, imaging, refractive optics aberration correction, coherent beam addition, and laser beam shaping. [6, 1, 2] Recently, a DOE that has become increasingly common in the same applications as the MDLs are metalenses. A metalens is formed by distinct assembly of nanostructures on a substrate, as shown in Figure 2(b). [3, 6] These nanostructures enable the lens to fine-tune the polarization of light to attain a higher focusing efficiency. Because of these structures and the complexity of the design, the production of this lens requires a high-cost nanofabrication.

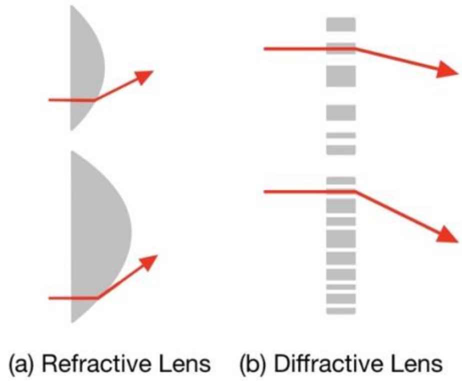

Figure 1. Demonstrates the bending of light with (a) refractive lenses of different thicknesses and (b) diffractive lenses.

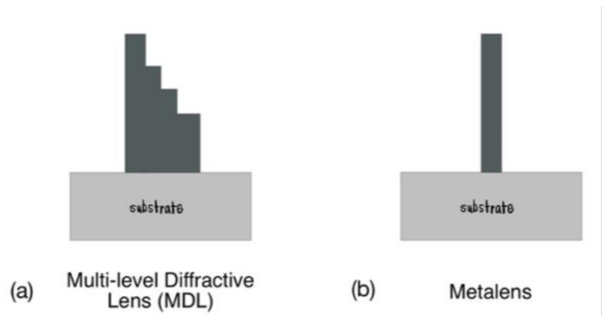

Figure 2. Schematic representation of a (a) multilevel diffractive lens (MDL) and (b) metalens.

Currently, the process of designing the MDL and metalens uses existing research and theories from the field of photonics and a simulation tool called CST Studio Suite to verify the performance of the designs before the lenses are fabricated. This process constrains the designs for the lenses to known correlations and optimizations to improve the focusing efficiency. Thus, this can be a drawn-out process and resources may be better directed elsewhere if the process were streamlined. A method of accelerating this process is through machine learning (ML).

Background

Machine Learning Algorithms

The widespread utilization of ML has aided and expedited the research process in photonics. Since ML is data-driven, the computer algorithms utilize the necessary data to train and develop the algorithms to extrapolate correlations. MI employs a standard set of steps to validate the application of ML and the generated material, as shown in Figure 3. In particular, the ML algorithms applied to the optimization of the MDL and metalens are neural networks (NN) and Bayesian optimization, respectively.

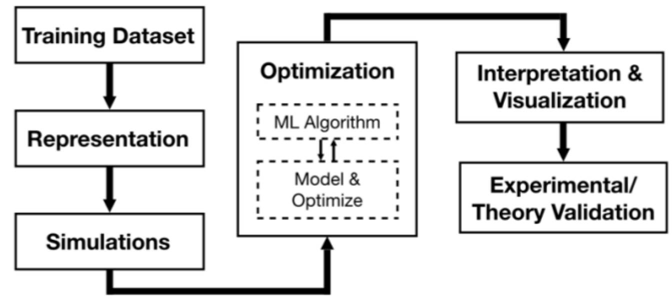

Figure 3. A general schematic for a MI discovery pipeline.

Neural Networks

NN is a collection of neurons, where the neurons closely resemble and function like the ones found in our bodies. As shown in Figure 4, a neuron is able to receive inputs at the input layer. The inputs are then processed in the hidden layer and sent to output layer of the neuron. The hidden layer processes the inputs by transforming them into inputs that are usable in the output layer. From there, the outputs in the output layer are delivered to the next neurons in the network. This sequence of events is repeated in the network until a decision is reached. Thus, NN reproduce the way a human brain learns and solves problems.

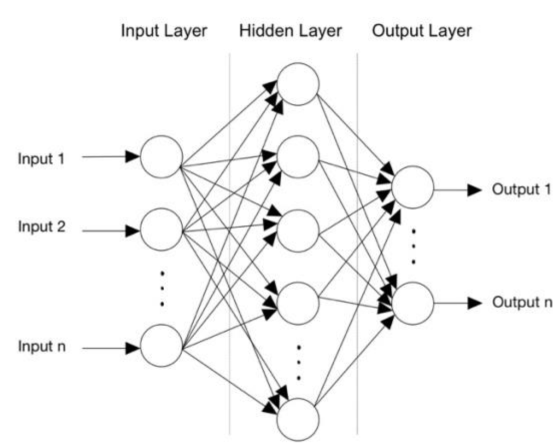

Figure 4. Schematic representation of a neural network.

Bayesian Optimization

Bayesian optimization is a design algorithm that applies a probabilistic approach to determine an approximated optimization for the black-box function. A black-box function is an unknown process between the input and output developed by the model of the approach. The optimal model is generated by hyperparameters, which are standards that supervise the learning process of the algorithm. In a simplified model, the algorithm takes an input that is funneled into a black box, which then generates an optimized output on the basis of predicted values and variances. [2]

Related Techniques for DOE Design

Multi-level Diffractive Lens (MDL)

For most DOE designs, the design technique applies the application of the Fresnel diffraction theory.[1] The theory utilizes mathematical interpretations that compute the behavior of the light wave at the desired location on the output plane of the substrate. The inputs to the NN are the distances between each of the concentric circles on the substrate and the input/output plane of the DOE. [1] Since the design is categorized as an optimization problem, a NN with one hidden layer allows the technique to have a low computational cost and complexity. Only one hidden layer is required because one is enough to encompass the output to an array of DOE designs. In a simplified model, a more complex problem requires more hidden layers and computational cost to determine the output. The output should be the architecture of the microstructures required to achieve the optimal focusing efficiency. [1]

Metalens

An artificially structured material that is engineered to possess desired properties over a broad range of wavelengths is classified as an electromagnetic metamaterial. To tailor an optimized electromagnetic metamaterial, the design of the nanostructures must identify a geometry that maximizes the objective properties. These properties include the modulation of heat conduction, identification of energetically stable structures, control of optical scattering and cloaking effects, optimization of thermal conductance and thermoelectric figure of merit. [2] As described in Figure 5, the objective properties are identified by a combination of electromagnetic simulation and Bayesian optimization to develop the most optimal electromagnetic metamaterial from the predicted metamaterials. An electromagnetic simulation tool is a software that is capable of modeling electromagnetic devices. In this case, the simulation tool has the ability to model the generated metamaterial and determine the objective properties.

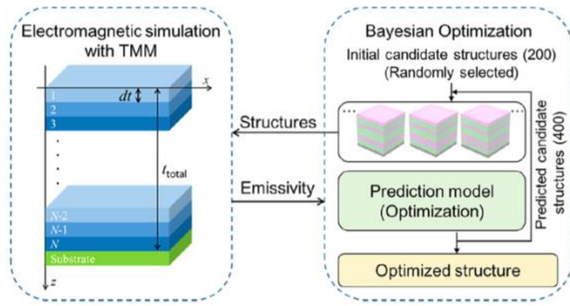

Figure 5. Schematic of the optimization method using electromagnetic simulation and Bayesian optimization.[2]

This technique involves the development of metamaterials with a user-specified number of layers with uniform thicknesses, where each layer can be either Germanium (Ge), Silicon (Si), and Silicon Oxide (SiO_2). After the predicted metamaterials are generated, the spectral emission from the metamaterial is computed using the simulation. An open-source library models the Bayesian optimization that is utilized to determine the optimized metamaterial. [2]

Proposed Techniques for DOE Design

Multi-level Diffractive Lens (MDL)

The related technique mentioned in the background pertains to a generalized solution for the design of DOEs. To make the solution adjusted for MDLs, the related technique will need to be slightly modified. The blazed phase structural architecture is unique to MDLs. They indicate the output architecture of the microstructures for the lens is already known. To maximize the focusing efficiency averaged over all wavelengths of interest, the height of the desired blazed phase structure on the MDL can be fine-tuned. [6]

The proposed modifications to the related technique would concern the inputs, outputs, and the NN algorithm. An additional input to the NN is the height of the blazed phase structures on the MDL. The revised output of the NN is the adjusted architecture of the MDL with an optimized focusing efficiency.

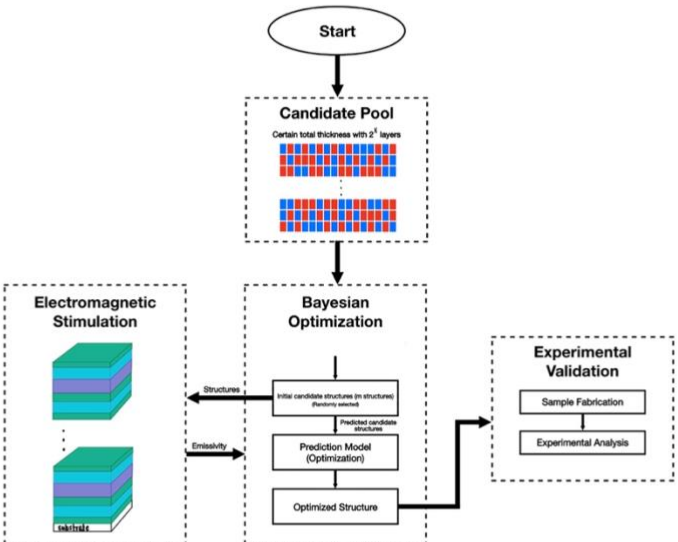

Figure 6. Schematic of the method for computationally designing an optimal metalens.

Metalens

Since metamaterials are the generalized form of metalens, the related technique detailed in the background needs to be modified to develop an optimized metalens. The modifications to the technique pertain to the unit layer elements, the electromagnetic simulation tools, and the addition of an experimental validation process. For the composition of the metalens, the unit layers will be assembled from the collection of compounds: Ge, Indium Phosphide (InP), Hafnium Oxide (HfO_2), or Silicon Nitride (Si_3N_4). These compounds are commonly found in photonic applications. To simulate the predicted metalenses, an additional simulation tool called CST Studio Suite will be used to model them. The remainder of the technique will be the same as the one described in the background with the addition of an experimental validation process. This validation process will incorporate fabrication and experimental analysis to ensure that the fabricated optimized metalens is comparable to the computationally designed one. The modified technique is shown in Figure 6.

Conclusion

Both of the proposed techniques consider ML as a powerful application that has the capabilities to generate optimized materials in an efficient and accurate manner. This paper serves as a proposal for techniques for the design of DOEs, specifically MDLs and metalenses. For further application of these techniques, the computationally designed MDLs and metalenses can greatly reduce the design time when these techniques have a low computational cost and complexity when compared to preexisting techniques in the field. In addition, these techniques can decrease the number of the fabrication and alignment issues that may not line up with the designed values, which can minimize the cost of fabrication. This can contribute to an acceleration of findings in the field of MI.

Acknowledgements

This work is being supported by MIT Lincoln Laboratory, Tom Vandervelde and Emily Carlson from the Renewable Energy and Applied Photonics Lab at Tufts University, and Ron Lasser, Department of Electrical and Computer Engineering.

References

1. Pasupuleti, A., Gopalan, A., Sahin, F., & Abushagur, M. A. G. (2004). Generalized design of diffractive optical elements using neural networks. *Proc. SPIEE 5579, Photonics North 2004: Photonic Applications in Telecommunications, Sensors, Software, and Lasers*. https://doi.org/10.1117/12.567191

2. Sakurai, A., Yada, K., Simomua, S. J., Kashiwagi, M., Okada, H., Nagao, T., Tsuda, K., & Shiomi, J. (2019). Ultranarrow-Band Wavelength-Selective Thermal Emission with Aperiodic Multilayered Metamaterials Designed by Bayesian Optimization. *ACS Cent. Sci, 5,* 219-326.

3. Engelberg, J., & Levy, U. (2020). The advantages of metalenses over diffractive lenses. *Nat Commun, 11,* 1991. https://doi.org/10.1038/s41467-020-15972-9

4. Jahns, J., & Walker, S. J. (1990). Two-dimensional array of diffractive Microlenses fabricated by thin film deposition. *Appl. Opt., 29,* 931-936.

5. Saal, J., Oliynyk, A., Meredig, & Bryce (2020). Machine Learning in Materials Discovery: Confirmed Predictions and Their Underlying Approaches. *Annual Review of Materials Research, 50.* 10.1146/annurev-matsci-090319-010954

6. Banerji, S., Meem, M., Majumder, A., Vasquez, F. G., Sensale-Rodriguez, B., & Menon, R. (2019). Imaging with flat optics: metalenses or diffractive lenses?. *Optica*, *6*, 805-810.