Project for Team 5

Title

Advanced Chiral Metasurface Engineering in the Mid-Infrared Region with Different Neural Network Approaches

Objective

The objective of this study is to develop advanced deep learning frameworks for the design and optimization of chiral metasurfaces operating in the mid-infrared region. The aim is to achieve customized chiral metasurfaces with tailored chiral optical properties, facilitating their applications in various fields such as sensing, imaging, and communication.

Description

Chiral metasurfaces, known for their ability to control the polarization of light, have attracted significant attention for their potential applications in the mid-IR spectrum. This study proposes an innovative approach that integrates neural network (NN) models into the metasurface design process. For this DL-GPU workshop, students in Team 3 are expected to implement the deep neural network into the design of chiral metasurface, aiming to simplify and accelerate the complex and time-consuming process of optimizing chiral metasurfaces, thereby enhancing their efficiency and functionality.

This project will be divided into three key stages:
1) Chiral Metasurface Simulation and Data Collection through Finite Element Analysis (FEA) Software: The first stage requires students to initialize a design of chiral metasurface and create a comprehensive dataset of chiral metasurface designs with different parameters and their corresponding optical responses. The commercial software of FEA that will be utilized is CST Studio Suite.
2) DNN Models Training and Prediction: The dataset from stage one will be used to train different types of NN models. Based on the performance of models, models such as RNN, GAN, TNN can be used for further testing. Students will use these models to predict the desired geometry parameters or optical responses via the NN models and verified by the FEA software.
3) Comparison of Model Accuracy and Computational Costs: In this stage, students will evaluate the performance of the trained NN models by comparing their accuracy in prediction of the desired geometry parameters or optical responses. Additionally, students will analyze the computational costs associated with training and running each model. This involves assessing factors such as training time, resource usage, and prediction speed, providing a comprehensive understanding of each model's efficiency and effectiveness.

Expected Outcomes

Students will understand how to design, optimize and implement NN models into the design process of chiral metasurface design. They will have a better understanding of the differences between NN models. In the future, they can dig deeper into this field with more complex model designs.

Reference

[1] Yeung, Christopher, et al. "Global inverse design across multiple photonic structure classes using generative deep learning." Advanced Optical Materials 9.20 (2021): 2100548.
[2] Yeung, Christopher, et al. "Multiplexed supercell metasurface design and optimization with tandem residual networks." Nanophotonics 10.3 (2021): 1133-1143.
[3] Hou, Zheyu, et al. "On-demand design based on deep learning and phase manipulation of all-silicon terahertz chiral metasurfaces." Results in Physics 42 (2022): 106024.
[4] Wang, Chenqian, et al. "Flexibly Designable 2D Chiral Metasurfaces with Pixelated Topological Structure Based on Machine Learning." Laser & Photonics Reviews (2024): 2300958.
[5] Luo, Chen, et al. "Flexible design of chiroptical response of planar chiral metamaterials using deep learning." Optics Express 32.8 (2024): 13978-13985.
[6] Mey, Oliver, and Arash Rahimi-Iman. "Machine learning-based optimization of chiral photonic nanostructures: evolution-and neural network-based designs." physica status solidi (RRL)–Rapid Research Letters 16.2 (2022): 2100571.
[7] Gupta, Aggraj, et al. "Tandem neural network based design of multiband antennas." IEEE Transactions on Antennas and Propagation 71.8 (2023): 6308-6317.

Project presentation: 30-minute team presentation on Friday, June 7th, 2024

Paper draft: an 8-page paper including references in the 2-column format using the latest ACM proceedings templates at https://www.acm.org/publications/proceedings-template . For Latex users, version 2.08 (last update June 4, 2024) is the latest template, and please use the "sigconf" option.
Paper draft completion deadline: August 2nd, 2024