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Neural Network Method for Dielectric Optical Coating Design

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We use neural networks to address the challenge of deriving dielectric coating designs from the desired optical properties. We show that our trained neural network can automatically design common laser mirror coatings types efficiently.

In the realm of dielectric optical coating engineering, optimizing thin-film layer designs to achieve desired optical function properties typically demands intricate optimization of layer thicknesses within layer stacks, posing a formidable inverse problem. Multi-layer optical coatings are ubiquitous for lasers and high level optical systems such as microscope objectives or telescopes as well as everyday items such as glasses, cameras, etc. While the physics of multi-layer coatings is well understood, deriving suitable designs from desired optical properties remains challenging. Currently, this task relies on expert intuition and conventional more or less brute-force numerical optimization methods [1-4] which do not explore the entire optimization space and have no guarantee of finding an optimal solution. Addressing this challenge, we propose to use neural networks to navigate the complex design space. Our predictive modeling framework utilizes neural networks to infer optimal layer stacks from a given reflectivity function $R(\lambda)$, where λ specifies the optical wavelength, effectively transforming the inverse problem into a differentiable optimization task. Using this methodology, we predict coating designs such as laser mirrors, anti-reflective coatings and pass filters with optical properties matching those obtained via conventional optimization methods.

We use a neural network trained on a rich design dataset encompassing a range of standard coating designs and properties commonly employed within ultrafast laser optics. We split the dataset into distinct training and testing subsets to prevent the network from being evaluated on data it has already encountered during training. Through comprehensive training, our model learns to generalize effectively on the test data. A critical component of our approach is a mathematical forward model, employing a classic transfer matrix approach, which accurately computes reflectivity $R(\lambda)$ from coating designs (see Figure 1). This forward model is used for visualization of the optical coating properties, enabling a direct comparison with coating designs obtained via conventional optimization methods [1].

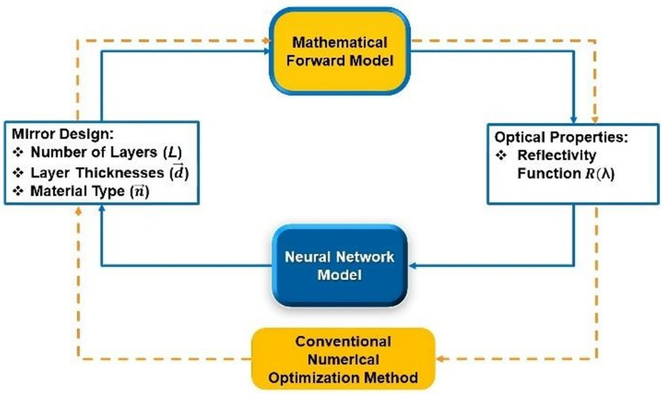

Fig. 1. Multilayer optical coating design: Conventional numerical optimization method (orange) and our approach based on Deep Neural Networks (Blue)

For network training, we employ well-established loss functions, including mean squared error (MSE) loss and cross-entropy (CE) loss, to quantify the disparity between the coating design predicted by the network and the ground truth coating design data. The optimization process is guided by the continual minimization of these loss functions, ensuring that the model iteratively refines its predictions to better align with the ground truth data. Additionally, we monitor the downward trend of the loss function values, indicative of the model's learning progress and convergence towards optimal solutions.

We conducted extensive testing of our model, an example data set is displayed in Figure 2, showing the coating reflectivity obtained via the forward model using the neural network prediction (blue). The network-based result agrees very well with the result obtained via conventional optimization methods (orange). Furthermore, the rapid solutions obtained by our deep neural network model may serve as improved initial designs for subsequent optimization or refinement processes, such as with the classical needle algorithm [2]. The data showed was obtained using the target regions displayed as input for both methods. The model used in this example is trained on a combination of different coating designs encompassing the following optical properties: high reflectivity (quarter wave stacks), anti-reflection effect and filters. Our training data sets are augmented by central wavelength shifting approaches bolstering the model’s resilience and adaptability across diverse scenarios.

Our ongoing efforts focus on two main areas. Firstly, we aim to expand our model by incorporating additional coating design data. Secondly, we are considering additional optical properties such as absorption, transmission, phase, and polarization. Additionally, we are conducting rigorous testing, not only on standard coating designs but also using arbitrary user inputs tailored to specific optical properties. Our efforts promise to expedite coating design processes catalyzing significant advancements in optical physics. Prospectively, this may enable to efficiently derive coating designs tailored to specific optical properties with unprecedented speed, accuracy and efficiency.

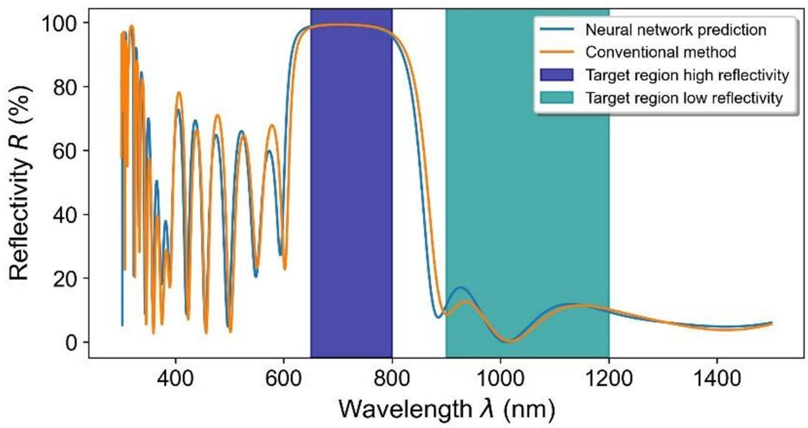

Fig. 2. Reflectivity comparison of optical long pass filter: the neural network result (blue) agrees very well with the result obtained via conventional optimization methods (orange)

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