Machine learning design of subwavelengh integrated photonic devices

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Abstract— **Use of subwavelength metastructures opens new degrees of freedom to control and manipulate propagation of light in planar waveguide devices. This advantage comes with the cost of increased design complexity since more parameters must be simultaneously optimized. Here we show how machine learning dimensionality reduction can be used to obtain a compact representation of a multi-parameter design space revealing the relationship between different design parameters. This provides the designer with a global perspective on the design space and enables informed decisions based on the relative priorities of different performance metrics.**

I. Introduction

The field of nanophotonics has been rapidly expanding, both in terms of new research directions and applications, including optical communications, sensing, and quantum computing [1-3]. Within this evolution trend waveguide devices based on subwavelength metamaterials are becoming established as fundamental building blocks for integrated photonic devices [4]. The novel optical properties these structures exhibit and the possibility to tune their optical responses are opening new prospects for controlling flow of light in planar waveguide circuits. Subwavelength grating metamaterials have been attracting a strong research interest in both academia and industry and many advanced devices with unprecedented performance have been demonstrated, such as fiber-chip couplers, ultra-broadband waveguide devices, Bragg filters with high spectral sensitivity and nanophotonic waveguides with engineered anisotropy [4].

The design of these subwavelength devices involves the complex control of the nanostructured (meta)material to obtain the required response and the simultaneous optimization of a large number of parameters that are often strongly inter-related. Classical design approaches based on sequential parameter sweeps and optimizations could hence fall short in finding the best design due to unachievable computational requirements. For this reason tools such as genetic algorithms, particle swarm, gradient-based optimization, and artificial neural network are increasingly used to search for high performance designs by varying many design parameters simultaneously [5]. Design approaches based on these tools often focus on finding a single optimized design with regard to a pre-selected performance metric and their outcome gives little insight on the interplay of different design parameters in determining the device performance. The ability to efficiently explore and comprehend large design spaces is still beyond reach.

Recently we have proposed the application of machine learning tools to address these challenges [6]. In this paper we report on the application of this strategy for the design of subwavelength nanophotonic devices with large number of parameters. We exploit dimensionality reduction to analyze the apparent degeneracy in a sparse set of possible designs with regard to a primary design objective. This provides a compact representation for an entire region of interest in the design space. At the same time, it allows the identification and visualization of patterns representing the interplay of multiple design parameters. The photonic designer can leverage this knowledge to obtain a global mapping of the design space, and balance various competing design requirements.

II. Mapping a multi-parameter design spaces

The goal of our design strategy goes beyond identification of a single design optimized for a specific performance metric. We aim to create a methodology to explore and map the design space. We demonstrate this for a high-dimensional design space considering as case study a perfectly vertical fiber grating coupler on a silicon-on-insulator (SOI) platform. The grating geometry is shown in Fig. 1. The grating period consists of two sections. The first section is a 220-nm-thick segment incorporating a subwavelength metamaterial, represented by an effective material index n_{swg} [7]. The second section is an L-shaped block, partially etched to 110 nm to achieve high directionality upwards (blazing effect). This geometry can simultaneously ensure a good fiber coupling efficiency and low back-reflections, a critical aspect for vertical grating coupler where second-order diffraction must be suppressed. Each possible design is identified by a vector $\mathbf{P}$ = [L1,L2,L3,L4,n_{swg}] including the structure dimensions L1 – L4 and the effective material index n_{swg}. This defines the five-dimensional design parameter space to be explored.

Our design flow comprises three main steps. First, we use a global optimizer to find a collection of different "good" designs whose fiber coupling efficiency is above 74% at wavelength λ = 1550 nm (close to state-of-the-art devices). This is our primary performance metric. For this purpose, we run an in-house line-search optimizer with random initial guess, albeit other global optimization tools such as genetic algorithm and particle swarm can also be used. In the second step we apply the dimensionality reduction technique within the unsupervised machine learning toolbox, to find the relationship between these good designs. Specifically, we use the principal component analysis (PCA), an unsupervised machine learning pattern recognition technique that has been used widely and successfully across various engineering and science disciplines and is implemented in most scientific computing platforms [8]. PCA is a linear technique that transforms a set of correlated variables into a smaller set of orthogonal variables that retain most of the original information. If a lower dimensional sub-space is found and validated to contain all good designs, the rest of the design space can be excluded from further investigations. This

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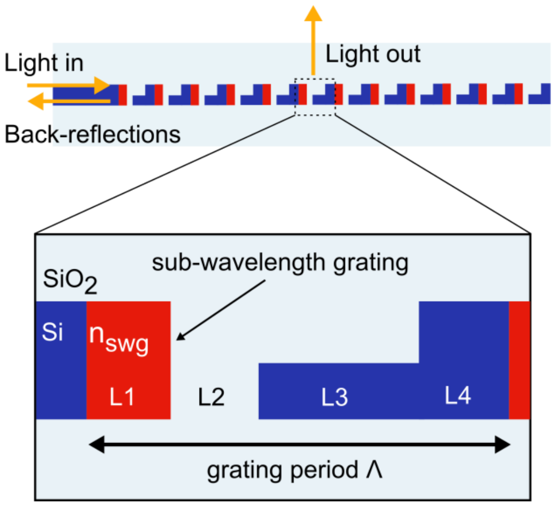

Fig. 1. Schematic representation of the vertical fiber grating coupler. The first section incorporates a subwavelength grating metamaterial, represented with an effective refractive index.

results in a reduction of both the number of parameters and the range of values that have to be evaluated.

From the collection of good grating designs obtained in the first stage, 5 different designs are sufficient for PCA to reliably reveal a two-dimensional subspace that contains all possible designs with state-of-the-art coupling efficiency. This means that a large part of the design space is no longer relevant and it can be excluded from further investigation.. The sub-space of *all good designs* is defined by two principal components, $\mathbf{V}_{1\alpha\beta}$ and $\mathbf{V}_{2\alpha\beta}$ and a constant vector $\mathbf{C}_{\alpha\beta}$ defining the reference origin. A good design candidate k can now be represented through two coefficients α and β as

$$\mathbf{P}_k = \alpha_k \mathbf{V}_{1\alpha\beta} + \beta_k \mathbf{V}_{2\alpha\beta} + \mathbf{C}_{\alpha\beta}. \quad (1)$$

This reduction from 5 initial parameters to 2 coefficients makes it feasible in the third and last step to adopt a more conventional design approach and perform an exhaustive exploration of the reduced parameter space, the α-β hyperplane. Any performance criteria can now be evaluated for all the designs included in the lower-dimensional sub-space with a few hundreds of simulation runs. Specifically, by mapping fiber coupling efficiency across the hyperplane, we discover a large and continuous area comprising all the good grating designs with coupling efficiency above 74%, including the sparse set of designs discovered through optimization in step 1. Despite being very different in their geometry, all the designs offer a similar high coupling efficiency, above 74%.

On the other hand, when back-reflections are considered and evaluated across the same continuous area, substantial differences in performance are discovered. For some of the grating designs back-reflections are as low as -40dB while for other parameter selections they increase almost to -15dB. This information is of fundamental importance for coupling to a laser.

Another important design aspect of the grating coupler is the minimum feature size. In order to ensure compatibility with large-volume production based on deep-UV lithography, minimum feature size should not be preferably smaller than 100 nm. This information can be easily retrieved through a query process computing equation (1) through the hyperplane without performing any additional photonic simulations. Across the area of good designs, minimum feature size changes dramatically and for some gratings it is a low as 40 nm. On the other hand, a sub-area of good designs is identified within which all the designs have a minimum size larger than 100 nm for each of the grating sections.

III. Conclusion

We have introduced a new design strategy leveraging machine learning technique to address arising challenges in nanophotonic design such as handling highly-dimensional design spaces and strongly inter-related parameters. Dimensionality reduction is used to reduce a large number of correlated design variables to a smaller set of orthogonal variables, significantly simplifying the design problem. This way, exhaustive mapping of design space can be achieved with modest computational resources. Multiple performance metrics can be quickly investigated, mapped and clearly visualized. This results in an intuitive understanding that gives the designer guidance to navigate the complex design space and make informed choice on the best final design.

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