Deep Neural Network Inverse-Design for Long Wave Infrared Hyperspectral Imaging

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Abstract **—** This paper presents a deep learning approach for the inverse-design of metal-insulator-metal metasurfaces for hyperspectral imaging applications. Deep neural networks are able to compensate for the complex interactions between electromagnetic waves and metastructures to efficiently produce design solutions that would be difficult to obtain using other methods. Since electromagnetic spectra are sequential in nature, recurrent neural networks are especially suited for relating such spectra to structural parameters.

Index Terms **─** Hyperspectral imaging, metal-insulator-metal, metasurface, narrowband filter, recurrent neural network.

I. INTRODUCTION

Hyperspectral imaging introduces an additional dimensionality to conventional imaging by measuring many narrowband channels of electromagnetic radiation emitted from each point on an object. This additional information can help distinguish otherwise unseen features of an object and aid in applications such as identification, diagnosis, and spectroscopy.

One of the main challenges with hyperspectral imaging is producing these narrowband channels so that they are highly efficient over their specified bandwidth, but also strongly reject any signals outside this bandwidth. Metallic structures are useful for satisfying the rejection criteria, but their lossy characteristics at infrared and optical frequencies tend to prohibit the high-Q response needed to produce highly transmissive narrowband windows. Dielectrics, on the other hand, can support high-Q resonances, but it is difficult to create broad rejection bands, since they are naturally transmissive. Metal-insulator-metal (MIM) metamaterials [1] have shown potential for overcoming these trade-offs, but the complexity of the structures makes it difficult to satisfy the necessary conditions for hyper-spectral imaging.

Deep neural network (DNN) approaches have begun to emerge as viable solutions for engineering metamaterial structures to produce specified functionalities [2-5]. Since electromagnetic spectra are sequential in form, recurrent neural networks are promising for solving inverse-design challenges in that they can efficiently map structural parameters to electromagnetic spectra. Specifically, we will demonstrate the use of DNNs to produce metasurface filters for hyperspectral imaging applications in the long wave infrared regime (9-11µm).

II. PROPOSED METASTRUCTURE AND DESIGN

Figure 1 shows the basic design of the metamaterial filter. We use a uniform slab of GaAs with patterned layers of Au structures on the top and bottom of the slab to form an (MIM) metasurface. By altering the unit cell size and the shapes of the Au structures across the surface, we can create separate passbands for different sections of the metasurface and form 20-40 channels spanning the 9-11 µm range. A metasurface divided into channels acts as single pixel for a hyperspectral image, with multiple metasurfaces being used to form a complete image.

III. DEEP NEURAL NETWORK APPROACH

The inverse design network is trained similarly to encoder/decoder networks, but in two separate steps. In the first step, a decoder network composed of LSTM layers is trained to predict transmission spectra from a set of structure parameters. Once the decoder network is trained, it is used to train an encoder network that takes transmission spectra as input and outputs structure

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parameters. This training occurs by cascading the decoder network after the encoder network but freezing training on the decoder network, as shown in Fig. 2 (a). The cascaded network takes a transmission spectrum as input and attempts to reproduce the same spectrum as output. Once properly trained, the encoder network is removed from the cascade and is now the desired inverse-design network (Fig. 2 (b)). This cascaded training method is essential to assuring that the encoder network will converge to a unique solution, since it's possible for a given transmission spectrum to be produced by multiple types of structures.

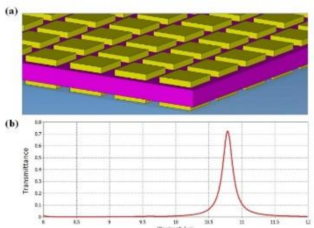

Fig. 1. (a) Metasurface filter composed of a slab of GaAs between layers of patterned Au structures. (b) Typical transmittance spectrum.

IV. DISCUSSION

The presented metal-insulator-metal design works by using the Au layers as diffraction gratings, which couple free space electromagnetic waves to surface plasmon polariton (SPP) resonance modes that occur at the GaAs/Au interfaces. These modes are less lossy than those that would occur in purely plasmonic structures and thus exhibit a higher-Q factor; as required for narrowband transmission. The dual gratings are essential, as wave vector conservation prohibits SPP modes from being directly excited by free space EM waves or from directly radiating into free space.

Given the complexity of this process, deep neural network techniques provide an efficient method for producing and realizing designs for complex metastructures, such as the MIM narrowband filter we have presented. A DNN can be trained from the results of full wave simulations, with ~10^4 structures needed to provide the training dataset. On the other hand, parameter sweeping methods would require several orders of magnitude more simulations to assemble a library of structures from which a matching design could be pulled. Such a design would likely require further optimization, whereas one produced by a fully trained DNN would already be locally optimal.

V. CONCLUSION

Hyperspectral imaging requires the creation of many narrowband channels to characterize the emission spectrum of an object. The channels can potentially be created by appropriate metamaterials, but the complex interactions between structures and electromagnetic waves make it difficult to satisfy the necessary criteria. We have proposed deep neural network approaches for the inverse-design of metal-insulator-metal narrowband filters to overcome these issues. Recurrent neural networks are particularly useful for obtaining accurate solutions to this problem so that an optimal design can be found.

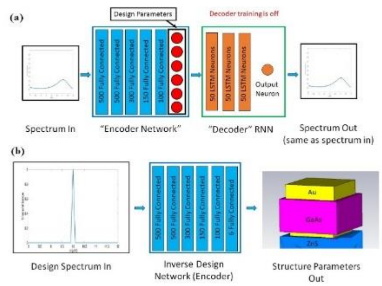

Fig. 2. (a) Cascaded training process for the inverse design network for narrowband Au/GaAs/Au metal-insulator-metal filters. The decoder recurrent neural network (RNN) is pre-trained separately to predict transmission spectra from structure parameters and then cascaded to an untrained encoder network. The combined network is trained to reproduce input transmission spectra at the output, with training for the decoder network turned off so that only the weights for the encoder network are adjusted during training. (b) The trained encoder network is detached from the cascaded network and is now capable of producing a set of MIM structure parameters from a transmission spectrum input.

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