Deep Learning Methods for Optimizing Terahertz Leaky Wave Antenna Design

J. Neronha, H. Guerboukha, and D. Mittleman

School of Engineering, Brown University, Providence, RI 02912

Introduction

The predictive power of neural networks and machine learning techniques more generally have been applied to a vast array problems ever since the neural network was proposed as a computational model for the brain in the mid-twentieth century. [1] This, of course, includes communications technology – neural networks have been used extensively in the field because of their unique ability to approximate accurate solutions to nonlinear problems that are commonplace in antenna design. Machine learning models are particularly useful in situations where an analytical solution cannot be obtained and/or numerical simulations are expensive [2, 3], for example when solving the "direct" problem of approximating an antenna's output [4] or modeling a metasurface [5], which could take a finite-element model hours or longer to solve, limiting real-time simulation and design. The "inverse" problem considers the opposite, for example reconstructing an image from scattered light [6].

We are particularly interested in the inverse problem of terahertz leaky-wave antenna (LWA) design because of its high applicability to the field of communications – given some arbitrarily desired far-field pattern, how can we quickly design, fabricate, and test an antenna that meets our needs? LWAs are simple metallic waveguides that have proven very effective in the terahertz range and are particularly interesting because they emit radiation at a frequency-dependent angle with a one-to-one relationship between frequency and angle, which is quite valuable given the narrow character of beams in the terahertz range. [7] They have been used in a number of diverse applications including link discovery [8], multiplexing and demultiplexing [9, 10], and for radar and object detection purposes [11]. Leaky-wave antennas also stand out for our purposes of rapid design and experimentation because of the ease of fabricating them using novel hot-stamping techniques [12].

This inverse problem has been explored in the terahertz range using deep neural networks in the context of designing structures to obtain an optimized geometry that produces the desired signal, particularly in relation to metasurface design [13, 14]. The inverse Leaky-wave antenna problem has also been explored, but using a genetic algorithm and outside of the terahertz range at much higher frequencies [15]. As a result, in this paper, we propose a model to predict the ideal LWA geometry that will generate desired far-field radiation in the terahertz range.

Methodology

We train a model to predict a slot geometry for a desired far-field signal. In particular, we consider a one-dimensional discretized slot where each component 0.5 micron slot can either be transparent or

metallic, similar to the approach taken in past explorations of metasurface design [15]. This design essentially creates a non-uniform periodic waveguide whose peaks can be predicted by Floquet theory. In a leaky wave guide with plate separation h, the dispersion constant β for a given period Λ and Floquet mode p for a wave vector k_0 is given by:

$$\beta = \sqrt{k_0^2 - (\frac{\pi}{h})^2} + \frac{2\pi p}{\Lambda} \tag{1}$$

Oftentimes, the primary objective design of antenna design is to generate peaks of specific magnitudes at specific locations. We use Eq. 1 to obtain the location of all possible Floquet peaks for periodic leaky wave antennas, which form the set of possible peaks for which the model can design a geometry. This is important because it ensures that users of the model cannot attempt to design a slot that will place a peak at an angle that is impossible given the dispersion relation for the waveguide. For our LWA with a plate separation of 1 mm operating at a frequency of 200 GHz, we plot the possible peaks generated by Floquet theory in Figure 1 below.

We build a model of a leaky-wave antenna in COMSOL Multiphysics with a slot of length 18 mm divided into 36 sub-slots, each of which is 500 microns in length. 18 sub-slots (exactly half) of the slots are randomly chosen as to be transparent (i.e. a scattering boundary layer) whereas the balance remain metallic and thus do not leak radiation. We automate this random geometry generation and simulation using MPh [16], an open-source Python package that enables controlling COMSOL via its native API.

Results and Discussion

Conclusion

References

[1] W. S. McCulloch and W. Pitts, "A logical calculus of the ideas immanent in nervous activity," *The bulletin of mathematical biophysics*, vol. 5, no. 4, pp. 115–133, 1943.

[2] Y. Kim, "Application of machine learning to antenna design and radar signal processing: A review," in *2018 International Symposium on Antennas and Propagation (ISAP)*, pp. 1–2, 2018.

[3] A. Massa, D. Marcantonio, X. Chen, M. Li, and M. Salucci, "Dnns as applied to electromagnetics, antennas, and propagation—a review," *IEEE Antennas and Wireless Propagation Letters*, vol. 18, no. 11, pp. 2225–2229, 2019.

[4] H. M. Yao and L. J. Jiang, "Machine learning based neural network solving methods for the fdtd method," in *2018 IEEE International Symposium on Antennas and Propagation USNC/URSI National Radio Science Meeting*, pp. 2321–2322, 2018.

[5] C. C. Nadell, B. Huang, J. M. Malof, and W. J. Padilla, "Deep learning for accelerated all-dielectric metasurface design," *Opt. Express*, vol. 27, pp. 27523–27535, Sep 2019.

[6] Y. Sun, Z. Xia, and U. S. Kamilov, "Efficient and accurate inversion of multiple scattering with deep learning," *Opt. Express*, vol. 26, pp. 14678–14688, May 2018.

[7] H. Guerboukha, R. Shrestha, J. Neronha, O. Ryan, M. Hornbuckle, Z. Fang, and D. M. Mittleman, "Efficient leaky-wave antennas at terahertz frequencies generating highly directional beams," *Applied Physics Letters*, vol. 117, no. 26, p. 261103, 2020.

[8] Y. Ghasempour, R. Shrestha, A. Charous, E. Knightly, and D. M. Mittleman, "Single-shot link discovery for terahertz wireless networks," *Nature Communications*, vol. 11, no. 1, p. 2017, 2020.

[9] N. J. Karl, R. W. McKinney, Y. Monnai, R. Mendis, and D. M. Mittleman, "Frequency-division multiplexing in the terahertz range using a leaky-wave antenna," *Nature Photonics*, vol. 9, no. 11, pp. 717–720, 2015.

[10] J. Ma, N. J. Karl, S. Bretin, G. Ducournau, and D. M. Mittleman, "Frequency-division multiplexer and demultiplexer for terahertz wireless links," *Nature Communications*, vol. 8, no. 1, p. 729, 2017.

[11] Y. Amarasinghe, R. Mendis, and D. M. Mittleman, "Real-time object tracking using a leaky thz waveguide," *Opt. Express*, vol. 28, pp. 17997–18005, Jun 2020.

[12] H. Guerboukha, Y. Amarasinghe, R. Shrestha, A. Pizzuto, and D. M. Mittleman, "High-volume rapid prototyping technique for terahertz metallic metasurfaces," *Opt. Express*, vol. 29, pp. 13806–13814, Apr 2021.

[13] Y. Deng, S. Ren, K. Fan, J. M. Malof, and W. J. Padilla, "Neural-adjoint method for the inverse design of all-dielectric metasurfaces," *Opt. Express*, vol. 29, pp. 7526–7534, Mar 2021.

[14] E. Dejband, J.-W. Li, P.-C. Peng, and T.-H. Tan, "Prediction of thz absorption and inverse design of graphene-based metasurface structure using deep learning," in *2021 30th Wireless and Optical Communications Conference (WOCC)*, pp. 21–23, 2021.

[15] S. Jafar-Zanjani, S. Inampudi, and H. Mosallaei, "Adaptive genetic algorithm for optical metasurfaces design," *Scientific Reports*, vol. 8, no. 1, p. 11040, 2018.

[16] J. Hennig, M. Elfner, and J. Feder, "Mph-py/mph: Mph 1.1.5," Feb. 2022.