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Douglas H. Werner, Series Editor

Advances in Electromagnetics Empowered by Artificial Intelligence and Deep Learning



Edited by
Sawyer D. Campbell
Douglas H. Werner

Advances in Electromagnetics Empowered by Artificial Intelligence and Deep Learning

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Edited by

Sawyer D. Campbell and Douglas H. Werner

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To the memory of my mother Joyce L. Campbell

—Sawyer D. Campbell

To my devoted wife Pingjuan Li Werner and to the memory of my grandmother Flora L. Werner

—Douglas H. Werner

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Preface

The subject of this book is the application of the rapidly growing areas of artificial intelligence (AI) and deep learning (DL) in electromagnetics (EMs). AI and DL have the potential to disrupt the state-of-the-art in a number of research disciplines within the greater electromagnetics, optics, and photonics fields, particularly in the areas of inverse-modeling and inverse-design. While a number of high-profile papers have been published in these areas in the last few years, many researchers and engineers have yet to explore AI and DL solutions for their problems of interest. Nevertheless, the use of AI and DL within electromagnetics and other technical areas is only set to grow as more scientists and engineers learn about how to apply these techniques to their research. To this end, we organized this book to serve both as an introduction to the basics of AI and DL as well as to present cutting-edge research advances in applications of AI and DL in radio-frequency (RF) and optical modeling, simulation, and inverse-design. This book provides a comprehensive treatment of the field on subjects ranging from fundamental theoretical principles and new technological developments to state-of-the-art device design, as well as examples encompassing a wide range of related sub-areas. The content of the book covers all-dielectric and metallo-dielectric optical metasurface deep-learning-accelerated inverse-design, deep neural networks for inverse scattering and the inverse design of artificial electromagnetic materials, applications of deep learning for advanced antenna and array design, reduced-order model development, and other related topics.

This volume seeks to address questions such as “What is deep learning?,” “How does one train a deep neural network?,” “How does one apply AI/DL to electromagnetics, optics, scattering, and propagation problems?,” and “What is the current state-of-the-art in applied AI/DL in electromagnetics?” The first chapters of the book provide a comprehensive overview of the fundamental concepts and taxonomy of artificial intelligence, neural networks, and deep learning in order to provide the reader with a firm foundation on which to stand before exploring the more technical application areas presented in the remaining chapters. Throughout this volume, theoretical discussions are complemented by a broad range of design examples and numerical studies. We hope that this book will be an indispensable resource for graduate students, researchers, and professionals in the greater electromagnetics, antennas, photonics, and optical communities.

This book comprises a total of 17 invited chapters contributed from leading experts in the fields of AI, DL, computer science, optics, photonics, and electromagnetics. A brief summary of each chapter is provided as follows.

Chapter 1 introduces the fundamentals of neural networks and a taxonomy of terms, concepts, and language that is commonly used in AI and DL works. Moreover, the chapter contains a discussion of model development and how backpropagation is used to train complex network architectures. Chapter 2 provides a survey of recent advancements in AI and DL in the areas of

supervised and unsupervised learning, physics-inspired machine learning models, among others as well as a discussion of the various types of hardware that is used to efficiently train neural networks. Chapter 3 focuses on the use of machine learning and surrogate models within the system-by-design paradigm for the efficient optimization-driven solution of complex electromagnetic design problems such as reflectarrays and metamaterial lenses. Chapter 4 introduces both the fundamentals and advanced formulations of artificial neural network (ANN) techniques for knowledge-based parametric electromagnetic (EM) modeling and optimization of microwave components. Chapter 5 presents two semi-supervised learning schemes to model microwave passive components for antenna and array modeling and optimization, and an autoencoder neural network used to reduce time-domain simulation data dimensionality. Chapter 6 introduces generative machine learning for photonic design which enables users to provide a desired transmittance profile to a trained deep neural network which then produces the structure which yields the desired spectra; a true inverse-design scheme. Chapter 7 discusses emergent concepts at the interface of the data sciences and conventional computational electromagnetics (CEM) algorithms (e.g. those based on finite differences, finite elements, and the method of moments). Chapter 8 combines DL with multiobjective optimization to examine the tradeoffs between performance and fabrication process uncertainties of nanofabricated optical metasurfaces with the goal of pushing optical metasurface fabrication toward wafer-scale. Chapter 9 explores machine learning (ML)/DL techniques to reduce the computational cost associated with the inverse-design of reconfigurable intelligent surfaces (RISs) which offer the potential for adaptable wireless channels and smart radio environments. Chapter 10 presents a selection of neural network architectures for Huygens' metasurface design (e.g. fully connected neural networks, convolutional neural networks, recurrent neural networks, and generative adversarial networks) while discussing neuromorphic photonics wherein meta-atoms can be used to physically construct neural networks for optical computing. Chapter 11 examines the use of deep neural networks in the design synthesis of artificial electromagnetic materials. For both forward and inverse design paradigms, the major fundamental challenges of design within that paradigm, and how deep neural networks have recently been used to overcome these challenges are presented. Chapter 12 introduces the framework of machine learning-assisted optimization (MLAO) and discusses its application to antenna and antenna array design as a way to overcome the limitations of traditional design methodologies. Chapter 13 summarizes the basics of uniform and non-uniform array processing using kernel learning methods which are naturally well adapted to the signal processing nature of antenna arrays. Chapter 14 describes a procedure for improved-efficacy electromagnetic-driven global optimization of high-frequency structures by exploiting response feature technology along with inverse surrogates to permit rapid determination of the parameter space components while rendering a high-quality starting point, which requires only further local refinement. Chapter 15 introduces four DL techniques to reduce the computational burden of high contrast inverse scattering of electrically large structures. These techniques can accelerate the process of reconstructing model parameters such as permittivity, conductivity, and permeability of unknown objects located inside an inaccessible region by analyzing the scattered fields from a domain of interest. Chapter 16 describes various applications of DL in the classification of radar images such as micro-Doppler spectrograms, range-Doppler diagrams, and synthetic aperture radar images for applications including human motion classification, hand gesture recognition, drone detection, vehicle detection, ship detection, and more. Finally, Chapter 17 explores the use of Koopman autoencoders for producing reduced-order models that mitigate the computational burden of traditional electromagnetic particle-in-cell algorithms, which are used to simulate kinetic plasmas due to their ability to accurately capture complicated transient nonlinear phenomena.

We owe a great debt to all of the authors of each of the 17 chapters for their wonderful contributions to this book, which we believe will provide readers with a timely and invaluable reference to the current state-of-the-art in applied AI and DL in electromagnetics. We would also like to express our gratitude to the Wiley/IEEE Press staff for their assistance and patience throughout the entire process of realizing this book – without their help, none of this would be possible.

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