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Machine learning based tandem network approach for antenna design

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***Abstract*—In this paper, we introduce novel machine learning based techniques to design multi-band microstrip antennas as per user specifications over a broad range of frequencies. The approach involves the design and training of a neural network for approximating the electromagnetic simulations of antennas, the so-called 'forward' problem. Here, the antenna is parameterized in terms of a checker-board pattern of metallic sub-patches. Additionally, a second 'tandem' neural network is also designed, which takes the user specification of a desired return-loss spectrum and returns an antenna structure. We explore the various machine learning innovations that are required in order for this approach to succeed. Our approach makes way for rapid designs of multi-band antennas, which is otherwise known to be a tedious task requiring vast domain knowledge.**

I. Introduction

Antennas are one of the most critical blocks at the front-end of any radio frequency (RF) system. Sophisticated functionalities in devices come with device complexity. Antenna design involves expensive and time consuming electromagnetic simulations. However, with the advances of machine learning techniques, data-driven approaches are emerging as a better paradigm for various photonic and RF design processes instead of conventional approaches. These new approaches offer the possibility of generalizing domain-specific tasks by "black-boxing" input/output relations, thereby bringing down the requirements of extensive domain knowledge.

In this paper, we propose neural network-driven methods for antenna design, expanding on our preliminary work [1]. The forward model predicts the return loss response (i.e. S_{11}) for a given microstrip antenna. Subsequently, given specifications of the *desired* performance of an antenna, the proposed approach is capable of designing compact and multi-band antennas.

Designing a device given a desired response is an emerging field of research seen recently in photonic devices. Recently, the backpropagation algorithm was used for the design of multi-layered nanophotonic particles with a desired absorption spectrum [2], [3]. Similarly, nanophotonic structures were designed with the help of deep learning [4]; here, a novel neural network solved the "data inconsistency" problem *which inherently exists in inverse electromagnetic problems* via a "tandem" architecture of neural networks for approximating device design. Our neural network based approach is inspired by this work, though with significant differences since the domain of the device specification is in discrete space, whereas in the original work it was in continuous space. However, no references have been found to optimize and design the microstrip patch antenna in the binary space using data-driven algorithms to obtain multi-band resonant compact antennas. A critical contribution of this research is the introduction of a new activation layer, so called *ST layer*, short for "Smooth Thresholding," which assists in the learning of a binary mapping from real-valued to discrete space.

In this paper, we use a convolutional neural network (CNN) framework for the forward modelling of the antennas and use this pre-trained network to assist a tandem network to design compact multi-band antennas. The proposed loss function for training the tandem antenna is inspired by earlier work [5], [6].

II. Methods

The overall framework for the antenna design is shown in Fig. 1.

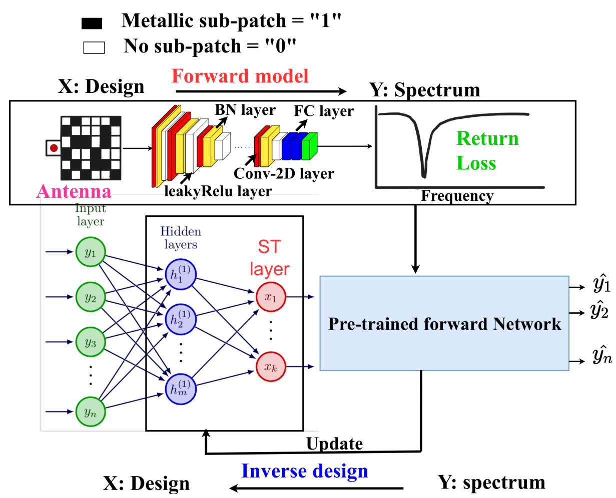

Fig. 1. Proposed architecture for the inverse design of the antenna. x_i represents the true design, y_i represents the true S_{11} response, $\hat{x_i}$ represents the predicted design and $\hat{y_i}$ represents the predicted S_{11} response. BN: Batch normalisation layer, FC: Fully-connected layer

A. Forward model

The dataset is generated using MATLAB to train our model; in order to keep the large simulation time at a minimum, these feature antenna structures with air rather than dielectric as the substrate. A square metallic area is divided into equal area, rectangular sub-patches, m, in number. Thus, the input vector x contains 1s or 0s depending on whether or not a sub-patch is to be metal or air, respectively. An element in the training set is generated by choosing x at random, and simulating its return loss spectrum, y, in MATLAB.

The forward model approximates the antenna parameters, given the antenna design, and is used as a *cheap to evaluate* surrogate model to simulate the pixelated antenna structures. This in turn replaces the full-wave solver, which is computationally expensive for simulating the response of the structure. The first application of the network is to see how well it approximates the simulation result on never before seen input (for e.g. see Fig. 2), and as can be seen, is quite successful.

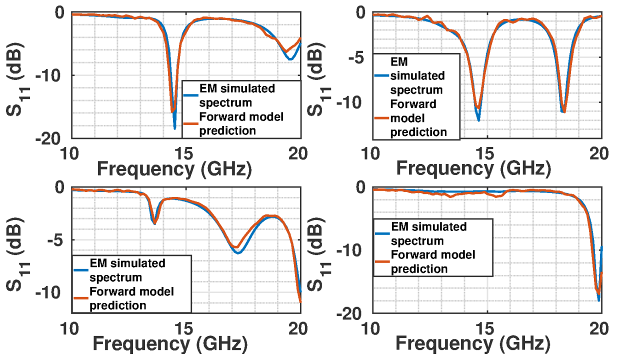

Fig. 2. Comparison of the forward model approximation and the full-wave solver response of the antenna

B. Inverse model

In this approach, we connect the layers to be trained to the pre-trained forward model (refer to Fig. 1). Our approach is inspired by the methodology of this paper [4], but unlike in our problem where the design is specified in terms of binary variables, the problem space here is continuous for both the input and output parameters. To address the issue of mapping a real vector to a binary vector, we introduce an "ST layer", short for Smooth approximation of a Threshold function, in the tandem network to map and learn the binary counterpart of the real design vector. This "ST" activation function is defined as $y = \frac{1}{2} + \frac{1}{2}\tanh m(x - \frac{1}{2})$, where "$m$" is an empirical parameter that controls the sharpness of the transition from 0 to 1. The function acts as follows – if $x \leq 0.5$, then $y \leq x$; if $x \geq 0.5$, then $y \geq x$, i.e. damping below 0.5 and amplifying above 0.5 as a means of forcing the output to be either 0 or 1. In addition, we add regularization terms to the loss function to further boost the probability of the design being in the binary space. An extensive study of the hyperparamters of the network has been carried out in support of the tandem network and its results.

III. Numerical results

Fig. 3 (top) shows a compact inverse designed single-band antenna using the proposed approach at 14 GHz. The inverse designed antenna is approximately 50% compact with respect to the conventional antenna at 14 GHz, with the same response as shown in Fig. 3 (bottom). Fig. 4 shows a compact inverse designed dual-band antenna using the proposed approach. It takes approximately $\approx$ 3 - 4 seconds to design the antenna once the tandem network is trained, which conventionally is a tedious task.

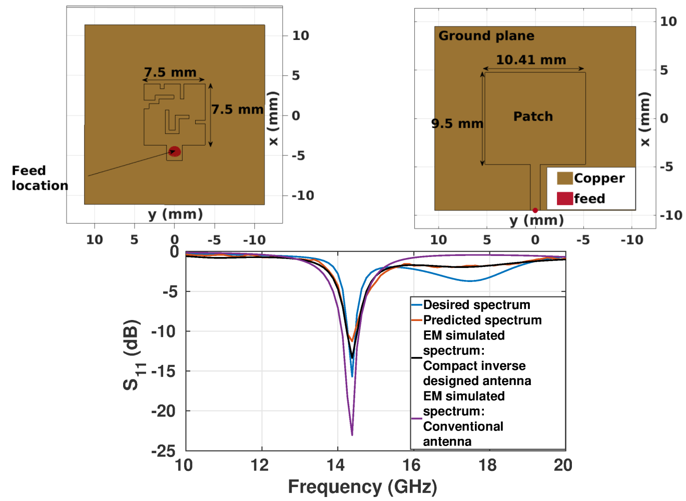

Fig. 3. Inverse designed single-band antenna (top left) and the Conventional antenna (top right): Compactness : 50% and comparison of the desired spectrum, predicted spectrum and the EM solver spectrum of the inverse designed antenna and the conventional antenna (bottom)

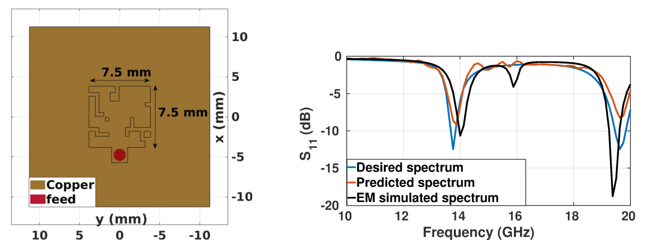

Fig. 4. Inverse designed dual-band antenna (left) and the comparison of the desired spectrum, predicted spectrum and the EM solver spectrum of the inverse designed antenna of a dual band antenna.

IV. Conclusion

In this paper, we have proposed a novel method for the inverse design of antennas. Specifically, we addressed the problem of designing miniaturized multi-band antennas with the help of deep learning. This approach is computationally time efficient when compared to the conventional methods of designing the antennas by commercial software.

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