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***Abstract*—Antenna designs play a crucial role in wireless communication systems where high-performance specifications are greatly required. The radiation pattern (RP) specification in both the E-plane and H-plane is important, as it connects the antenna gain along a given direction. This performance is calculated in the entire bandwidth for various frequencies and is time-consuming. To speed up these simulations, a new approach with the help of a generative adversarial network (GAN) is presented, leading to the prediction of the expected radiation pattern outcomes for the determined frequencies. This method is verified for two previously optimized antennas, one operating between 8.8–10.1 GHz and the other working in the 11.3–13.16 GHz band. The experimental simulation results prove that the mean absolute error is less than 0.35, which yields suitable accuracy for RP predictions.**

I. Introduction

In antenna designs, the term ‘radiation pattern (RP)’ presents the directional dependence of the power density of the radio waves radiated by the source. Typically, the amplitude is considered, but in some cases, the phase of the signal is also required [1]. Usually, collecting the signal amplitude and phase of antennas is not straightforward. Recently, diverse methods such as Fourier transform [2], element-level pattern diversity (ELPD) technique, and various optimization methods have been presented, leading to the analysis of the RPs [3]. However, synthesizing RPs with these methods for both E- and H-planes requires considerable computation time. To tackle this problem, recently intelligent-based methods have been presented in which deep neural networks [4] have proved their effectiveness in various antenna designs.

Deep learning (DL) is based on artificial neural networks, and the generative adversarial network (GAN) is a type of DL network that leads to creating data as the input real data. This study is devoted to employing the GAN network to predict the RP of antennas for both E- and H-planes at various frequencies. Firstly, an accurate model is trained by specifying the model loss function and training options. Afterward, the new data (i.e., RP) is predicated through the trained model. For proving the effectiveness of the proposed method, the RPs of two optimized antennas (presented in [4]) at 0° and 90° are considered, and the GAN network is trained and constructed for predicting the specific schematic of RP at the determined frequencies. The proposed method facilitates long-lasting RP simulations and can estimate the RP features for specific frequencies.

This paper is organized as follows: Section II presents the proposed methodology leading to predicting the RP of antenna for diverse frequencies. Section III describes the practical implementation of the method in the passive antennas, and finally, Section IV concludes this paper.

II. Proposed Methodology

The GAN network was initially developed by Ian Goodfellow in 2014 [5] for predicting generative models. It leads to constitute images, text, audio, and video that are analogous to real data. This section is devoted to presenting the application of the GAN network in the RP images achieved from passive antenna simulations.

The general structure of the GAN network is presented in Fig. 1 in which a custom training loop is excused and includes ‘Generator’ and ‘Discriminator’ networks. The input of the generator network includes random vectors leading to generated data, namely training data. From another side of view, the discriminator network produces data from both a) training data and b) generated data from the generator. As the output of this network, the observations are classified as either ‘real’ or ‘generated’ [6]. In summary, the generator produces new data, and the discriminator evaluates whether the data is ‘real’ from the training data or ‘fake’ from the generator. The generator and discriminator work against each other until the generator can create realistic data.

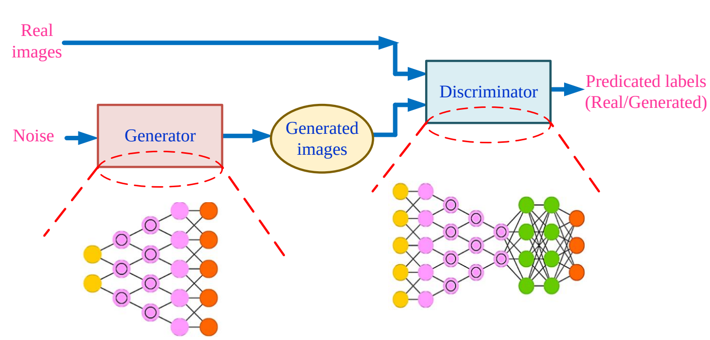

Fig. 1. Typical diagram of GAN structure.

As presented in Fig. 1, the real images as the training data are first inserted into the neural network in which the image datastore is created and resized. After determining the filter size with the number of filters, the network is ready for training the network with a custom training loop.

After defining the two networks (i.e., generator network and discriminator network), the training options for ‘epochs’ numbers with minimum batch size are specified. The validity of the GAN network must be calculated using the accuracy specification. To calculate the accuracy of the trained GAN network, related loss functions with scores for both discriminator and generator networks must be determined.

III. Simulation Results

To prove the effectiveness of the proposed method, we simulate two antennas at the frequency band of 8.8–10.1 GHz and 11.3–13.16 GHz, respectively, and intend to predict RPs for these antennas at specific frequencies. This section is devoted to presenting the practical implementation of the proposed methodology leading to the prediction of the RPs for determined frequencies.

As it is known, training any neural network needs a sufficient amount of training data. For this case, various RPs at E- and H-plane are extracted for diverse values of design parameters at different frequencies. Afterward, the proposed network is trained based on the presented structure in Fig. 1. The target of the trained network is to predict the RPs of passive antennas in E- and H-plane for various determined frequencies.

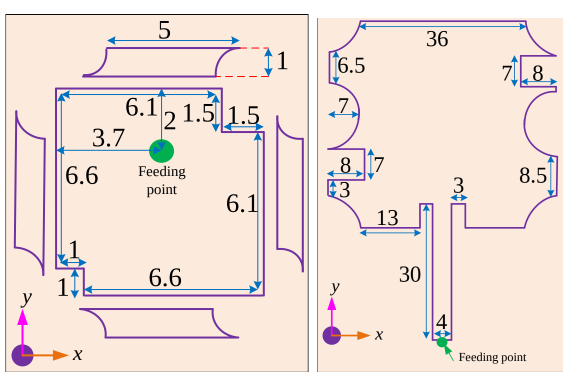

Fig. 2. Optimized antennas in [4]; Antenna-1 (left), Antenna-2 (right).

The proposed methodology is executed on the two optimized antennas in [4]. Fig. 2 reports the structures of antennas in which the suitable amount of training data (here, 500 RP images) is achieved by iterating the values of design parameters and getting the related RPs for each one. For both of the designs, three specific frequencies are selected. Hence, the proposed GAN network in this study targets the selection of the center frequency and the external limits of the band of interest. In the generator network, the filter size and number of filters are defined as 5 and 64, respectively. In the discriminator network, the number of filters is set to 64 as well. Fig.s 3 and 4 present the practical implementation of the proposed method for two optimized antennas depicted in Fig. 2. This methodology can prove that the consumed simulation time for RPs can be reduced effectively since RPs for determined

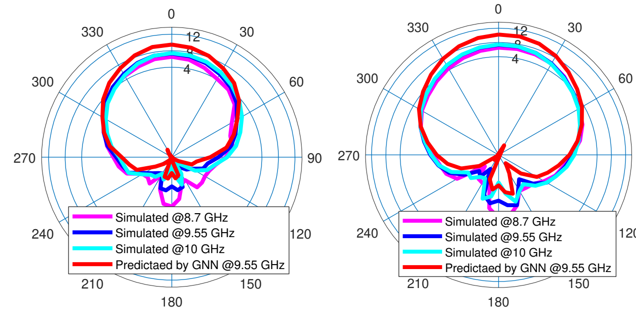

Fig. 3. RPs for antenna-1 at $\phi = 0$ (left), $\phi = 90^\circ$ (right).

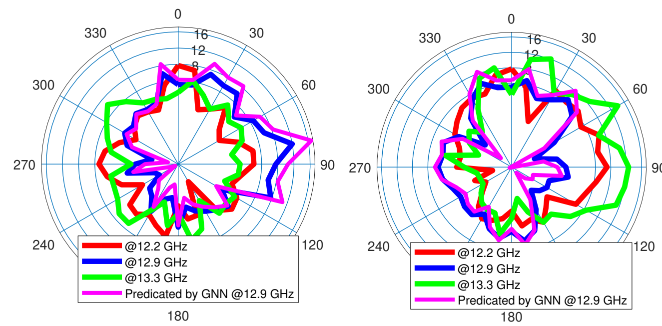

Fig. 4. RPs for antenna-2 at $\phi = 0$ (left), $\phi = 90^\circ$ (right).

frequencies can be predicted with a mean absolute error of less than 0.35 through the GAN networks.

IV. Conclusion

This study provides the practical implementation of deep learning image completion technique through a GAN network for extrapolating the RPs of passive antennas. The proposed approach predicts the RPs of passive antennas for E- and H-plane at center frequencies. This methodology will facilitate the simulations devoted to extracting the RPs that are significantly time-consuming.

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