Estimation of Electrical Characteristics of Inhomogeneous Walls Using Generative Adversarial Networks

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Abstract—Through-wall radars are researched and developed for the detection, localization, and tracking of human activities in indoor environments. Electromagnetic wave propagation through walls introduces refraction, attenuation, multipath, and ghost targets in the radar signatures. The estimation of wall characteristics (dielectric profile and thickness) can enable wall effects to be deconvolved from through-wall radar signatures. We use generative adversarial networks (GANs) to estimate wall characteristics from narrowband scattered electric fields on the same side of the wall as the transmitter. We demonstrate that the GANs, consisting of two neural networks configured in an adversarial manner, are capable of solving the highly nonlinear regression problem with limited training data to estimate the dielectric profile and thickness of actual walls up to 95% accuracy based on training with simulated data generated from full-wave solvers.

Index Terms—Dielectric constant, electromagnetic inverse scattering, generative adversarial networks (GANs), through-wall radar.

I. INTRODUCTION

THROUGH-WALL and indoor radars have been widely researched for human activity detection and recognition for various applications, such as security and surveillance, search and rescue, assisted living, and fall detection [1], [2]. Based on the type of radar, radar signatures could be micro-Doppler spectrograms obtained from joint time–frequency representations of time-domain narrowband radar data [3], [4], high-range resolution profiles generated from broadband data [5], and range–Doppler ambiguity diagrams generated from stepped-frequency continuous-wave radars or frequency-modulated continuous-wave radars [6] or range–azimuth signatures obtained from noise radars [7], [8]. The advantages of the narrowband radar are that these radars can be implemented with low-cost custom-off-the-shelf components, are low noise, and have high Doppler resolution that enables the detection and recognition of dynamic target activities [9], [10]. Broadband radar data, on the other hand, when gathered from large real/synthetic antenna apertures, can be processed to localize targets in range, azimuth, and elevation [11], [12]. However, when these radars are deployed in through-wall scenarios, the radar signals undergo complex propagation phenomenology such as attenuation, ringing, refraction, and multipath that result in ghost targets and other types of significant distortions in the radar signatures [4]. Walls are considerably diverse from single-layer homogeneous dielectric walls commonly found indoors to inhomogeneous/multilayered exterior walls. Similarly, wall materials can range from wood, cement, brick, stone, and mud to cinder blocks with air gaps.

In radar literature, different strategies have been explored to handle wall-based distortions on radar signatures. One strategy is to remove wall distortions—particularly front face reflections and refraction—through signal processing methods based on the complete or incomplete knowledge of wall characteristics (dielectric constant and thickness) [13], [14]. This strategy is particularly effective if the wall is a single-layer homogeneous and symmetric dielectric wall. More recently, sparsity-based deep learning methods have been exploited for removing wall effects without the requirement of any knowledge of wall characteristics [15], [16], [17], [18], [19]. However, these methods are predicated on the availability of a large volume of radar data of targets in free space and through-wall conditions. A third strategy is to exploit the multipath introduced by through-wall propagation to improve the radar detection performance [20], [21]. Other strategies have involved adapting hardware parameters to suppress wall effects [22], [23]. In all these studies, the focus has been on detecting and localizing targets behind the walls. In this article, we focus on a fifth strategy. Here, we use learning algorithms to directly estimate wall characteristics—thickness and dielectric profile—in the absence of targets from the radar data. The purpose of estimation of the wall electrical characteristics is to subsequently use the model for deconvolving wall effects from through-wall radar signatures of targets.

The estimation of wall characteristics from electromagnetic field data is a classical electromagnetics inverse scattering (EIS) problem [24]. Traditionally, EIS problems have been tackled using deterministic approaches, such as the Born approximation method (BAM) [25] and backpropagation (BP) [26], [27]. However, these techniques are known to provide poor accuracy, especially when the region of interest consists of scatterers with high dielectric constants. Iterative microwave imaging methods, such as the Born iterative method (BIM) [28], the distorted BIM [29], the contrast source-type inversion method [30], and the subspace optimization method [31], [32], have also been explored. These are time consuming and often not suitable for...
real-time reconstruction. These approaches are further complicated by the requirement of heuristic tuning of parameters for optimizing the performance of the algorithms. Alternatively, stochastic approaches involving genetic algorithms or particle swarm optimization [33] have been researched. These methods are computationally complex in terms of time and memory, and the complexity further scales with the degree of inhomogeneity in the region of interest. Hence, these methods have generally been ineffective in solving problems where the walls are inhomogeneous and dispersive due to the nonlinear relationship between the wall characteristics and the scattered fields.

Machine learning methods have been explored for a wide variety of EIS-based applications, such as microwave imaging, ground penetration radar, remote sensing, and biomedical imaging [34]. The challenges faced for the inverse problems using machine learning are limited data and high accuracy requirements. Artificial neural network (ANN)-based methodologies have also been used to extract information about the geometric and electromagnetic properties of scatterers [35], [36]. However, most of these methods represent scatterers with only a few parameters, such as their sizes, positions, shapes, and relative permittivities, and cannot be used when there is significant inhomogeneity.

In the past few years, convolutional and deep neural networks (DNNs) have been researched for solving highly nonlinear and ill-posed problems. DNNs are a flexible representation of high-dimensional nonlinear functions and have been explored for through-wall radar imaging [37], [38], [39]. The main challenge in the use of these algorithms is the requirement of large and correctly labeled training data gathered in diverse experimental settings. Generative adversarial networks (GANs), which have emerged from the deep learning community, consist of two networks that work in a zero-sum game. The two networks—generator and discriminator—could be either ANNs or convolutional neural networks (CNNs) [40], [41], [42]. GANs have been shown to be versatile in modeling/mapping highly nonlinear relationships between the input and output without requiring computationally expensive Markov chains. They have been used for a variety of tasks, such as data augmentation [43], image classification [44], reconstruction of high-resolution images from low-resolution images [45], spatiotemporal fusion [46], [47], and design synthesis [48]. The advantage of the GAN over other generative models, such as Boltzmann machines, is its ability to rapidly generate several realistic samples in parallel. In our problem statement, they provide the advantage of requiring small datasets during training compared to other algorithms with single networks. This is extremely important for real-world applications where they may be significant diversity in wall characteristics, and it may be practically impossible to train an algorithm for every possible wall type that may be encountered during radar deployment.

Recently, GANs have been applied for solving EIS methods [49]. The main objective of this article is to use GANs to estimate the permittivity profile and thickness of inhomogeneous walls based on simple radar measurements that can be easily carried out with custom off-the-shelf components. Specifically, the radar configuration consists of a continuous-wave narrowband, linearly polarized source excitation, and scattered fields that is measured at multiple receiver locations on the same side as the transmitter in the absence of targets on the far side. We examine GANs configured with both ANNs and CNNs and with time (real-valued) and frequency-domain (complex-valued) electric field data as input. Due to the challenges in gathering large volumes of training data, we use simulated data of scattered electric fields to train the GANs, which we subsequently use to estimate the characteristics (thickness and dielectric profile) of actual walls. We believe ours is the first work to estimate characteristics of real-world walls based entirely on training the learning algorithm with simulated data. We benchmark our proposed method with three classical electromagnetic techniques, i.e., BAM, BIM, and BP, and two popular machine learning techniques using a single neural network, i.e., the fully connected neural network (FC-NN) and the CNN. The BAM and BP utilize the integral electric field formulation to estimate the dielectric characteristics. The BIM introduces a regularization operator and iteration between the forward scattering and the inverse scattering problem formulations. We apply all these state-of-the-art techniques to the exact same simulation problem as the proposed GAN techniques to study their effectiveness. The data and algorithms are provided to the interested reader at https://essrg.iiitd.edu.in/?page_id=4355. We demonstrate that we can correctly estimate the thickness of the walls up to 95% and the dielectric constant profile within 97%, showcasing the versatility of the GAN-based algorithms for EIS problems. We find that the chief limitation of the approach is when the wall material is largely transparent to source frequency resulting in very low scattered fields at the same side as the transmitter.

The rest of this article is organized as follows. In Section II, we describe four different methods for configuring GANs for estimating wall properties from the scattered electric field. In Section III, we describe the experimental setup for generating simulated data that are subsequently used for training the GANs and subsequently validating the GANs using test simulated data. Once validated, the GANs are tested on measurement data from actual walls. The experimental setup for gathering measurement data and the measurement results are presented in Section V. Finally, Section VI concludes this article.

II. METHODOLOGY

The objective of this article is to estimate the thickness and electrical characteristics of walls based on their scattered electric field. We apply the following constraints to this problem statement. First, we assume a 2-D Cartesian problem space, as shown in Fig. 1, where the wall is illuminated by a narrowband vertically polarized electric field \( E_2^z \) from a single transmitter. The scattered field from the wall is measured at multiple receiver locations on the same side as the transmitter \( E_2^z, n = 1 : N \). In this problem formulation, it is assumed that the walls are infinitely long and uniform along \( z \) but may be inhomogeneous along \( x \)- and \( y \)-dimensions. The 2-D framework is chosen to reduce the computational complexity of the problem and because most walls show homogeneity along the height. Second, we assume that there are no targets on the far side of the wall...
In the fourth and final approach, we configure the two GAN networks with CNN and time-domain electric field data as input to the generator. The generator network is configured with two hidden layers with 512 and 256 hidden nodes, while the discriminator architecture is the same as GAN-ANNf. While training the generator, the weights and biases of the generator network are updated by keeping the discriminator constant. Similarly, while training the discriminator network, the weights and biases of the discriminator network are updated, keeping the generator weights constant. The training process involves iterative simultaneous stochastic gradient descent based on Adam optimization [51]. Since the loss function of each network depends on the other network’s parameters, but each network cannot control the other network’s parameters, the scenario is a zero-sum game. The training iterations are continued till the mean square loss error between the fake dielectric profiles generated by the network and the real dielectric profile converges to a low value. Further discussion on the convergence of the networks is provided in Appendix A. During the test stage, we provide test electric field $E_z$ along with random noise to the generator to estimate the actual dielectric profile $\epsilon_r$, as shown in Fig. 2(b). This is compared with GT data for validation.

### B. Network Details

We implement the GAN-based electromagnetic inversion through multiple and evaluate the effectiveness of each approach.

1) **GAN-ANNf:** In the first method, we configure the two networks with ANNs. We consider the narrowband frequency-domain complex-valued scattered electric field at the receivers as input to the GAN. The generator network is configured with two hidden layers with 256 and 512 hidden nodes and the leaky ReLU as an activation function. The tanh activation function is used in the output layer with 1024 nodes. The discriminator network consists of two hidden layers with 512 and 256 hidden nodes, with leaky ReLU activation functions. The output layer has one node with a sigmoid function.

2) **GAN-CNN:** In the second approach, we use time-domain electric field data as input to the generator. The generator consists of two hidden layers with 512 and 768 hidden nodes, while the discriminator architecture is the same as GAN-ANNf.

3) **GAN-CNNf:** In the next approach, the ANNs in the generator and discriminator are replaced by CNNs, while the frequency-domain electric field data are retained as input to the generator. Here, we have two hidden layers with 128 filters each of $4 \times 4$ kernel size with a stride of $2 \times 2$ in the generator, while in the discriminator, we have two hidden layers with 128 filters each of $3 \times 3$ kernel size with a stride of $2 \times 2$.

4) **GAN-CNNt:** In the fourth and final approach, we configure the two GAN networks with CNN and time-domain electric field as input to the generator. In the generator, the leaky ReLU conditional variant of the standard GAN since it uses labeled electric field data and corresponding dielectric profiles as input. This framework is noted for its greater stability [50]. Together, both the networks of the GAN work in an adversarial manner where the weights of the generator and discriminator are optimized based on a value function $V(G_\theta, D_\phi)$ as given in

$$\min_{G_\theta} \max_{D_\phi} V(G_\theta, D_\phi) = \min_{G_\theta} \max_{D_\phi} \log(D_\phi(\epsilon_r)) + \log(1 - D_\phi(N + E_z)) \quad (1)$$

While training the generator, the weights and biases of the generator network are updated by keeping the discriminator constant. Similarly, while training the discriminator network, the weights and biases of the discriminator network are updated, keeping the generator weights constant. The training process involves iterative simultaneous stochastic gradient descent based on Adam optimization [51]. Since the loss function of each network depends on the other network’s parameters, but each network cannot control the other network’s parameters, the scenario is a zero-sum game. The training iterations are continued till the mean square loss error between the fake dielectric profiles generated by the network and the real dielectric profile converges to a low value. Further discussion on the convergence of the networks is provided in Appendix A. During the test stage, we provide test electric field $E_z$ along with random noise to the generator to estimate the actual dielectric profile $\epsilon_r$, as shown in Fig. 2(b). This is compared with GT data for validation.
function is used for the hidden layers and tanh for the output layer. The generator has two hidden layers with 128 filters each. The first layer consists of $5 \times 5$ kernel size with a stride of $1 \times 1$, while the second layer consists of $3 \times 3$ kernel size with a stride of $2 \times 2$. The discriminator architecture is the same as GAN-CNNf.

The networks are configured with a 0.0002 learning rate and 0.2 dropout rate for all the cases. The network parameters discussed here are chosen based on thumb rules with respect to the size of the input and output vectors to the GAN and experimental results. The full details of the experiments are presented in Appendices B and C.

### III. Simulation Setup

In this section, we describe the simulation method to generate scattered electric field data from different types of walls. Wall materials can be wood, cement, brick, stone, mud, or cinder. Hence, the relative dielectric constants of various materials have been reported to vary from 2 to 8 in literature [52], [53], [54], [55]. The scattering phenomenology is modeled using finite-difference time-domain (FDTD) techniques [56]. We consider a 2-D simulation space spanning $-1.25$ to $1.25$ m along $x$ and $-0.25$ to $2.25$ m along the $y$-direction, as shown in Fig. 3. For each of these wall types, we consider multiple instances with distinct dielectric constants and thicknesses, as specified in Table I. For each simulation case, the values for the dielectric constants and the thicknesses are sampled from uniform distributions whose limits are provided in the table.

The first wall type is a homogeneous dielectric wall with relative permittivity, $\epsilon_r$, and thickness, $th$. The second wall type...

| WALL TYPE | PARAMETER | VALUES | CASES | TOTAL CASES |
|-----------|-----------|--------|-------|-------------|
| Homogeneous | $\epsilon_r$ | 3-8 | 26 | 130 |
| Y-layered wall | $\epsilon_{r_1}$ | 2-3 | 3 | |
| | $d_1$ | 10-30 cm | 5 | |
| | $d_2$ | 5-15 cm | 3 | 225 |
| X-layered wall | $\epsilon_{r_1}$ | 4-8 | 5 | |
| | $\epsilon_{r_2}$ | 2-3 | 3 | 225 |
| | $l_2$ | 60-80 cm | 5 | |
| | $l_1$ | (2 − $l_2$)/2 | | |
| | $th$ | 10-50 cm | 5 | |
| Wall with air gaps | $\epsilon_r$ | 3-8 | 26 | |
| | $th$ | 20-50 cm | 4 | |
| | air gaps | 2-4 | 3 | 312 |
is an inhomogeneous wall with three dielectric layers aligned in the y-direction corresponding to a dielectric wall with insulation materials/facades on either side. The inner layer of thickness \(d_2\) corresponds to a higher dielectric constant \((\varepsilon_{r_2})\) than that of the two outer layers \((\varepsilon_{r_1})\) of thickness \(d_1\). The third type of wall is the inhomogeneous wall with three dielectric layers aligned along the x-direction. This corresponds to dielectric walls with windows or doorways. Again, the two outer layers are assumed to have an identical length \(l_1\) and dielectric constant \((\varepsilon_{r_1})\), while the inner layer of length \(l_2\) has a higher dielectric constant \((\varepsilon_{r_2})\). The thickness of the wall \((th\ along\ y)\) is also varied in this case. The last wall type is a dielectric wall with periodic air gaps corresponding to cinderblock walls. Furthermore, we vary the total number of air gaps across the length of the wall from 2 to 4 while maintaining a constant edge thickness of 10 cm. Altogether, we consider 892 distinct wall cases, and the details of the entire dataset are available at https://essrg.iiitd.edu.in/?page_id=4355.

We consider an infinitely long line source excitation corresponding to the transmitter at \((0, m, 0.5)\). The source consists of a sinusoidal excitation at 2.4 GHz (corresponding to the frequency of operation of several through-wall radars that operate on the unlicensed bands [1]) and gives rise to transverse magnetic wave propagation in the 2-D space. The simulation space is bounded by a perfectly matched layer of \(2\lambda_c\) thickness, where \(\lambda_c\) corresponds to the wavelength. The entire 2-D space is discretized into uniform grids that are one-tenth the wavelength resolution. The electric field propagates from the source and impinges upon the wall. Some of the energy propagates through the wall, while the remaining is scattered. The time-domain electric field is recorded along with a uniform linear array at a specified standoff distance behind the front face of the wall, as indicated in the figure, where the elements are spaced half-wavelength apart (which is commonly chosen to prevent grating lobes) from \(-0.28\) to \(+0.28\) m. The duration of the simulation is set as 21.5 ns with a time resolution of 0.02 ns to ensure Courant stability conditions [57].

The FDTD operation is then repeated for free space conditions with the same source excitation, and the electric field is recorded at the ten receiver positions. Then, the electric field of the free space scenarios is subtracted from that of the wall scenarios in order to remove the direct coupling between the transmitter and the receivers.

The time-domain electric field data at each of the receiver positions are downsampled by a factor of 20 to obtain 52 time samples. The downsampling operation is carried out to reduce the complexity of the deep learning architecture. Note that since the source excitation is 2.4 GHz, the downsampling operation does not result in aliasing. The data from the ten receiver positions are concatenated to form a single column vector of \([520 \times 1]\) size. This is concatenated with a latent Gaussian noise vector of \([2000 \times 1]\) size of zero mean and unity variance and provided as the input to the generator for the GAN-ANNt and GAN-CNNt. For the frequency-domain variants of the GAN (GAN-ANNf and GAN-CNNf), we perform Fourier transform on the time-domain (before downsampling) electric field at the ten receiver positions and then extract the complex components corresponding to 2.4 GHz, which are provided as input to the generator. The real part of the fields is concatenated with the imaginary parts of the field to form a \([20 \times 1]\) vector, which is concatenated with a noise vector of size \([100 \times 1]\) and provided as input to the generator.

The dielectric profile corresponds to a spatial extent of the 2-D Cartesian space spanning \(x\) from \(-1\) to \(+1\) m and along the y-direction from 1 to 1.8 m with a spatial resolution of 0.01 m. Note that the spatial resolution for the GAN is higher than the spatial resolution of the FDTD grid space and corresponds to \(32 \times 32\) pixel size of the dielectric profile. The higher resolution profile of the FDTD space results in a much higher computational cost of the GAN and, hence, is not adopted. In ANN architectures (GAN-ANNt and GAN-ANNf), the output from the generator is mapped to the fake dielectric profile of size \([1024 \times 1]\) (2-D matrix reshaped to a column), while in the CNN architectures (GAN-CNNt and GAN-CNNf), the output retains the 2-D pixel structure. The spatial extent of the mapped dielectric profile in the y-direction of 0.8 m is greater than the thickness of most real-world walls and chosen so as to enable the estimation of the actual wall thickness. Of the total 892 data samples, we divide the dataset between training and validation. The batch size is taken as 16, and the model is trained for 1000 epochs.

IV. SIMULATION RESULTS

In this section, we evaluate the effectiveness of the proposed algorithms for estimating wall characteristics. We validate our GAN networks with test data—simulated electric field data \((\vec{E}_r)\) from walls with known dielectric profiles \((\varepsilon_r)\). The test data are fed to the generator from which we estimate the dielectric profile \((\varepsilon_r)\), which is subsequently compared with the GT dielectric profile.

A. Comparison of GAN With DNNs and Classical Methods

We evaluate the four methods of GAN that we discussed in the previous section—GAN-ANNt, GAN-ANNf, GAN-CNNt, and GAN-CNNf. We compare their performances with two other popular deep learning networks—the FC-NN and the CNN. Both these architectures consist of only a single neural network as opposed to the two adversarial networks used in the GAN. We also compare the performances with three classical EIS methods—BAM, BIM, and BP—for frequency-domain input data. We evaluate the results both visually and quantitatively.

1) Frequency Domain: First, we present the qualitative results for a test case for each wall type with frequency-domain electric field data as input. In Fig. 4, we present the dielectric profiles estimated for four wall cases—homogeneous, Y-layered wall, X-layered wall, and wall with air gaps. For each case, the GT dielectric profiles are presented in the first row. In the instance presented in Fig. 4(a), the dielectric constant of a 40-cm-thick homogeneous wall is 5.4. In Fig. 4(b), \((\varepsilon_{r_1} = 3, l_1 = 10\ cm)\) and \((\varepsilon_{r_2} = 5, l_2 = 25\ cm)\). In Fig. 4(c), \((\varepsilon_{r_1} = 2, d_1 = 60\ cm)\) and \((\varepsilon_{r_2} = 5, d_2 = 80\ cm)\). In Fig. 4(d), the wall has a dielectric constant of 5.6 and is 30 cm thick. It has three air gaps with an edge thickness of 10 cm. The second to fourth rows present the results obtained from BP, BAM, and BIM. For all cases of the wall, the estimated dielectric constant lie between...
Fig. 4. Reconstructed dielectric profiles of (a) homogeneous wall, (b) Y-layered wall, (c) X-layered wall, and (d) wall with air gaps in row II to VIII from BP, BAM, BIM, FC-NN, CNN, GAN-ANNf, and GAN-CNNf algorithms respectively with frequency domain input data.

1 and 2.5, which is well below the GT values, and the estimated thickness is not accurate. The results are most erroneous for the wall with air gaps. These results are consistent with the findings in the literature that report the poor performance of classical inverse scattering approaches at estimating high dielectric constants even in homogeneous conditions [26]. In the FC-NN and CNN results in the fifth and sixth rows of Fig. 4, we observe that the reconstructed dielectric profiles for all four cases are closer to the GT than the classical techniques. The thicknesses of the walls are estimated correctly, except for walls with air gaps. However, the estimate of the dielectric constant shows considerable error. We consider the reconstructed profiles generated by GAN-ANNf in the seventh row of Fig. 4. Here, we can see that the dielectric constant estimates lie between 4.5 and 5, and the estimated thickness is mostly accurate with slight distortion. Furthermore, in the case of the Y-layered wall, we see that the thicknesses of layers are estimated accurately. In the case of the X-layered wall, the thicknesses and dielectric profiles are estimated correctly. The same is mostly true for the wall with air gaps with the dielectric constant estimate ranging from 5 to 7 and thickness of 30 cm. Next, we consider the reconstructed profiles generated by GAN-CNNf in the eighth row of Fig. 4. Here, we can see that the dielectric constant estimates lie between 5 and 6, and the estimated thickness is mostly accurate. Furthermore, in the case of the Y-layered wall, we see that the thicknesses of layers are accurate. In the case of the X-layered wall, the dielectric profile is estimated correctly. Also, the wall with air gaps was estimated accurately, having a dielectric constant ranging from 5 to 6 and a thickness of 30 cm.

2) Time Domain: Next, we consider the time-domain data as input and consider the performance of the three algorithms, i.e., FC-NN, GAN-ANNt, and GAN-CNNt, in Fig. 5. The top row shows the GT for a single test case of each wall type. All three classical EM inversion techniques use Green’s function based on the frequency domain and, hence, cannot be used on the time-domain data. The results for FC-NN for all four wall cases show that the thickness of the wall is estimated somewhat correctly, but the estimates of the dielectric constant are always well below the actual values. The CNN results in the third row show a slightly better performance but are still not able to estimate the thickness of the profiles accurately. For example, the air gaps in the last case are not accurately reconstructed. In the GAN-ANNt results in the fourth row of Fig. 5, we can see that the dielectric constant estimates for the homogeneous wall lie between 5 and 6, and the estimated thickness is mostly accurate. Furthermore, in the case of the Y-layered wall, we see that the thicknesses of layers are accurate. In the case of the X-layered wall, three distinct wall regions are correctly reconstructed, and the thickness and dielectric constants are also fairly accurate.

Fig. 5. Reconstructed dielectric profiles of (a) homogeneous wall, (b) Y-layered wall, (c) X-layered wall, and (d) wall with air gaps in row II to V from FC-NN, CNN, GAN-ANNt, and GAN-CNNt algorithms respectively on time domain input data.
The estimated thickness of the wall with air gaps is lower than the GT. However, the air gaps are reconstructed correctly. We observe that the GAN-CNNt performs better in comparison to other methods in the fifth row of Fig. 5. Here, we see that the dielectric constant is estimated accurately for all four cases. The same is also true for the thickness except for the wall with air gaps, where the thickness estimate is a little higher than the GT. In conclusion, we observe visually that the GAN-based methods reconstruct the GT dielectric profiles more accurately than the classical methods and machine learning techniques with a single neural network.

For the quantitative comparison, the normalized mean square error (NMSE) is computed between the GT ($\epsilon_r$) and estimated dielectric profiles ($\hat{\epsilon}_r$) using

$$\text{NMSE} = \frac{\|\epsilon_r - \hat{\epsilon}_r\|_2^2}{\|\epsilon_r\|_2^2}. \quad (2)$$

The NMSE is computed across 90 test cases of data comprising all four types of walls. The quantitative comparison of the techniques for all the test cases is summarized in Table II. In Table II, the input data to the algorithm are either time- or frequency-domain data denoted as $t$ or $f$, respectively. The results show that the NMSE for the classical EIS techniques is much poorer than for the machine-learning-based techniques. The BP is slightly superior to the BAM. The BIM introduces iterations in the dielectric profile estimation of the BAM algorithm. This improves the performance slightly. The classical methods are unable to handle the high dielectric profiles in the scattering region. We also see that the proposed GAN methods are more accurate than FC-NN and CNN in obtaining lower NMSE, indicating that the use of two adversarial networks as opposed to one during training enables more accurate inversion operation. The GAN-CNNt network performs better than the same network with the frequency-domain input (GAN-CNNf). It is possibly because of the information loss in the operation where the complex-valued data in the frequency domain are separated into real and imaginary parts and then concatenated and provided as input. Also, GAN-CNNt, GAN-CNNf, and CNN networks achieve lower NMSE than their ANN counterparts, indicating the strength of CNNs in capturing nonlinear relationships. In all of these cases, 90% of simulated data are used for training, and the remaining are used as test data. Now, we test the robustness of the algorithms to the diversity in the data through two means. First, we test the performance when a smaller volume of simulation data is used for training. We changed the percentage of samples used for training from 60% to 90% in Fig. 6. In each case, the samples that are not used for training are used for validation. The result shows that the average NMSE improves for all the algorithms as the training percentage increases. The improvement is, however, most noticeable for the two single neural network frameworks (FC-NNf, FC-NNt, CNNf, and CNNt) and far less significant for the GAN frameworks (GAN-CNNf, GAN-CNNt, GAN-ANNf, and GAN-ANNt) indicating the advantages of the proposed framework in handling the data diversity.

Next, we train the networks with data gathered from three types of walls and test on data collected from the fourth wall. The results obtained from fourfold cross validation for all the different networks are presented in Table III. The results again show a lower average NMSE error for the four GAN frameworks compared with the other single neural network frameworks. This indicates that the GAN frameworks demonstrate greater generalization potential due to their robustness in handling diversity in test and training data. The effect of different types of noise distributions on the GAN performance is also studied in Appendix D.

### B. Computational Complexity

We report the training and testing times for the algorithms in Table II. The computation cost in training and testing the learning algorithms arises from basic operations performed within the networks, like convolution, addition, and calculation of activation functions. It also depends upon the number of layers, the types of layers, and the number of filters used in the neural networks. The classical EIS algorithms require no training. During the test, the BIM is much longer than the BAM due to the iterations within the algorithm till convergence is reached. In the case of the ANN architecture found in GAN-ANNt and GAN-ANNf, the complexity is of order $O(N^4)$ for $N$ stochastic gradient iterations for $N$ layers each with $N$ neurons and $N$ addition and multiplication operations [58]. The computation cost of FC-NN and CNN architecture is less than the GAN versions, which have two networks to train instead of one. Therefore, we note in Table II that the training times required by the GAN methods are comparatively greater than those of

### Table II

#### Benchmarking Proposed GAN-Based Inversion With Classical EIS Methods and Single-Neural-Network Methods

| Method   | Input type ($t/f$) | NMSE     | Training Time (min) | Testing Time (s/min) |
|----------|--------------------|----------|---------------------|---------------------|
| BP       | $t$                | 0.74     | -                   | 20s                 |
| BAM      | $f$                | 0.83     | -                   | 3 min               |
| FC-NN    | $t$                | 0.42     | 30-45               | 0.1s                |
| FC-NN    | $f$                | 0.40     | 30-45               | 0.1s                |
| CNN      | $t$                | 0.25     | 30-45               | 0.1s                |
| CNN      | $f$                | 0.26     | 30-45               | 0.1s                |
| GAN-ANNf | $t$                | 0.20     | 150-180             | 0.015s              |
| GAN-ANNf | $f$                | 0.17     | 150-180             | 0.015s              |

Fig. 6. Comparison of methods for different percentages of data divided for training and verification.
TABLE III
FOUR CROSS VALIDATIONS FOR DIFFERENT TYPES OF WALLS: 1) HOMOGENEOUS; 2) Y-LAYERED WALL; 3) X-LAYERED WALL; AND 4) WALL WITH AIR GAPS

| Training Wall Types | Testing Wall Type | FC-NN | FC-NN | CNNt | CNNt | GAN ANNf | GAN ANNf | GAN CNNt | GAN CNNt |
|---------------------|------------------|-------|-------|------|------|----------|----------|----------|----------|
| 1,2,3               | 4                | 0.49  | 0.49  | 0.45 | 0.45 | 0.26     | 0.22     | 0.21     | 0.20     |
| 1,2,4               | 3                | 0.44  | 0.44  | 0.35 | 0.35 | 0.25     | 0.20     | 0.21     | 0.21     |
| 1,3,4               | 2                | 0.45  | 0.44  | 0.40 | 0.42 | 0.25     | 0.24     | 0.22     | 0.20     |
| 2,3,4               | 1                | 0.42  | 0.43  | 0.35 | 0.38 | 0.24     | 0.22     | 0.20     | 0.19     |
| Avg. NMSE           | 0.43             | 0.45  | 0.40  | 0.40 | 0.25 | 0.22     | 0.21     | 0.20     |

TABLE IV
EXPERIMENTAL RESULTS FOR LOSSY WALL WITH AIR GAPS

| Conductivity (S/m) | GAN-CNNt | GAN-CNNf | GAN-ANNf | GAN-ANNf |
|--------------------|----------|----------|----------|----------|
| 0                  | 0.17     | 0.20     | 0.25     | 0.23     |
| 0.001              | 0.53     | 0.48     | 0.57     | 0.56     |
| 0.01               | 0.59     | 0.47     | 0.59     | 0.66     |
| 0.10               | 0.67     | 0.54     | 0.83     | 0.79     |
| 1                  | 0.68     | 0.57     | 0.81     | 0.80     |
| 10                 | 0.94     | 0.93     | 1.20     | 0.90     |

FC-NN and CNN, GAN-CNNt and GAN-CNNf have a CNN architecture, and their complexity is $O(MNk^2 IO)$ [59], [60]. Here, the number of the input and output feature maps is $I$ and $O$, respectively, $M \times N$ is the size of the feature map, and $k \times k$ is the convolution kernel size. Thus, this algorithm takes the longest time to train. In the testing phase, the generator in the four different GAN methods is required to do a single forward process to obtain the reconstructed result without iterations. In our work, since the GAN architecture has few filters and hidden layers and because the multiple profiles are generated in parallel, the testing time for the GAN-based algorithm is lower than that of FC-NN and CNN. Thus, the proposed techniques offer high accuracy with comparable low computational time during the test. The training and test codes are run with Keras 2.7 and trained and tested on an Intel Core i7-10510U processor running at 1.80 GHz.

C. Unexpected Test Conditions

In all of our discussions so far, we have considered test scenarios that correspond to conditions that satisfy the initial assumptions in the problem statement. Now, we study how the algorithm performs when unexpected scenarios are encountered during test conditions. Specifically, we consider two cases. First, when the wall is lossy, and second, when a target is present along with the wall.

1) Lossy Walls: Most building wall materials are measured to have conductivities ranging from 0.01 to 0.1 S/m [61], [62]. For our test case, we consider the wall with air gaps with a thickness of 40 cm having a dielectric constant varying uniformly between 4 and 8. We have taken five different values of conductivity, as shown in Table IV, and observed the outcome for the algorithms.

We observe that the errors are small when the conductivity is low—mirroring most real-world conditions. However, as we increase the value of conductivity, the NMSE deteriorates for all four variants of the GAN algorithm. This loss in performance can be attributed to the narrowband scattered electric field data that are gathered in our method, which do not provide information regarding dispersive materials in the scattering region of interest. We anticipate an improvement in the performance when wideband data are used for inversion.

2) Presence of Target: We have considered a rectangular target on the other side of the wall, as shown in Fig. 7. We considered the wall with air gaps wall having a dielectric value of 4 and targets of five different sizes and at five different positions behind the wall resulting in a total of 25 test samples of the scattered electric field from the wall with the presence of the target. We observe that the average NMSEs for GAN-ANNf, GAN-ANNt, GAN-CNNf, and GAN-CNNf are 0.4, 0.42, 0.35, and 0.31, respectively. Hence, we can conclude that, in the presence of the target, our proposed algorithm’s performance is slightly degraded but is still able to estimate the electrical characteristics of the walls. As previously noted, we observe that the GAN-CNNt and GAN-CNNf outperform the GAN-ANNf and GAN-ANNf due to the CNN architecture.

V. MEASUREMENT RESULTS

In this section, we use the GAN trained with the simulated electric field data of the previous section to estimate the dielectric profiles of real walls. In other words, we use scattered electric field data measurements from actual walls as input to the generator, and the output is the estimate of the dielectric profile of the wall. Note that it is not possible to get the exact GT dielectric profile of the walls. Instead, we get a rough estimate based on the known materials used to construct the wall.

A. Measurement Setup

First, we describe the measurement setup used to collect narrowband scattered electric fields from different types of walls. The radar setup, shown in Fig. 8(a), consists of a two-port vector
network analyzer Field Fox N9926A configured to make $S_{21}$ scattering parameter measurements at 2.4 GHz. The transmitted power is set at 3 dBm, and the sampling frequency of the measurement is 377 Hz. We replicate the simulation setup as closely as possible by placing the transmitter 50 cm from the wall and gathering scattered electric fields from positions 20 cm before the front face of the wall. A linearly polarized broadband horn antenna (HF907) and a dipole antenna are connected to the two ports. The scattered signal from the wall is captured by the VNA, where it is amplified, in phase-quadrature demodulated and digitized. Then, the complex VNA measurements are collected and downloaded to a laptop for further processing. We linearly move the dipole antenna to collect the data samples at ten positions corresponding to the receiver array discussed in the previous section. We consider four different walls, as shown in the figure. They are two exterior walls and one interior wall of a building, and one boundary wall from the perimeter of the campus, as shown in the figure. The first exterior wall is a 30-cm-thick brick wall with concrete and paint on either side. The second exterior wall is a 40-cm brick wall with concrete on one side and a very thin layer of ceramic tiles having a thickness of 10 mm forming a facade on the other side. The third wall is a perimeter boundary wall made of large stones and concrete. Due to the irregular arrangement of stones, this wall is the most inhomogeneous. The quantitative results are presented in Table V. Here, we observe that GAN-ANNf and GAN-CNNf with FC-NN and CNN. Due to the poor performance of the classical EIS methods on ideal simulated data, we do not use implement those methods with the measured data gathered from walls with high dielectric profiles. The reconstructed dielectric profiles of the four walls are shown in Fig. 9. The dielectric profile is reconstructed from the neural networks trained with simulation data. The first row shows the reconstructed dielectric profiles from the FC-NN, while the second row shows the results from CNN and the third row shows the results from GAN-ANNf, and the fourth row shows the results from GAN-CNNf. The result shows that the GAN-based method is able to reconstruct the dielectric profile for the two exterior and one interior wall fairly well, unlike the FC-NN and CNN. The most challenging case is the perimeter stone wall, which is highly inhomogeneous. The quantitative results are presented in Table V. Here, we observe that GAN-ANNf and GAN-CNNf estimated the thickness of the walls with an error ranging from 2.5% to 12.5%, and the corresponding range of the dielectric

Fig. 8. (a) Experimental radar setup before different types of wall. (b) 30-cm-thick exterior brick and concrete wall. (c) 40-cm-thick exterior brick wall with a thin facade of ceramic tiles. (d) 40-cm-thick perimeter boundary wall made of large stones and concrete. (e) 25-cm-thick interior brick and concrete wall.

Fig. 9. Dielectric profiles of real walls reconstructed from neural networks. (a) 30-cm-thick exterior brick and concrete wall. (b) 40-cm-thick exterior brick wall with a thin facade of ceramic tiles. (c) 40-cm-thick perimeter boundary wall made of large stones and concrete. (d) 25-cm-thick interior brick and concrete wall.

B. Results

In the previous section, both time- and frequency-domain electric field data were provided as input to the networks. The time-domain scattered electric field data were obtained from full-wave electromagnetic solver-based simulations at a sampling frequency of 9.6 GHz. In real-world conditions, gathering data at such high sampling frequencies is challenging due to constraints on the available analog-to-digital converters in the receivers. In our case, our experimental setup with a two-port Agilent N9926A vector network analyzer allows for a maximum sampling frequency of 377 Hz in the time-domain mode. Hence, we have carried out inverse scattering processing with the frequency-domain configuration as opposed to the time-domain mode and compared the performance of the GAN-CNNf and GAN-ANNf with FC-NN and CNN. Due to the poor performance of the classical EIS methods on ideal simulated data, we do not use implement those methods with the measured data gathered from walls with high dielectric profiles. The reconstructed dielectric profiles of the four walls are shown in Fig. 9. The dielectric profile is reconstructed from the neural networks trained with simulation data. The first row shows the reconstructed dielectric profiles from the FC-NN, while the second row shows the results from CNN and the third row shows the results from GAN-ANNf, and the fourth row shows the results from GAN-CNNf. The result shows that the GAN-based method is able to reconstruct the dielectric profile for the two exterior and one interior wall fairly well, unlike the FC-NN and CNN. The most challenging case is the perimeter stone wall, which is highly inhomogeneous. The quantitative results are presented in Table V. Here, we observe that GAN-ANNf and GAN-CNNf estimated the thickness of the walls with an error ranging from 2.5% to 12.5%, and the corresponding range of the dielectric
In all of our studies, the walls have been assumed to be uniform along with the height. Hence, the scattered electric field has been gathered across a linear array to capture the diversity in the wall characteristics across the 2-D Cartesian space. In scenarios where it is anticipated to have nonuniform characteristics across the height, the receivers can be placed along different heights to capture the effects of inhomogeneity along with the height. Furthermore, we have assumed that the dielectric constant of the walls is real. When the dielectric constant is complex, the wall properties become dispersive. We believe the complex electrical characteristics can be estimated from scattered fields that arise from wideband source excitation instead of the narrowband source excitation assumed in this article. The study of more complex walls and the corresponding excitation will form the focus of future works. In this article, we have focused on reconstructing the dielectric profiles of the regions beyond the front face of the wall. These regions may comprise multiple layers of inhomogeneous walls including other dielectric bodies (such as indoor furniture), provided that suitable training data are provided to the networks. We have only restricted the scenario to static conditions where there are no temporal variations in the scattered electric field due to dynamic bodies. The estimation of the profiles of dynamic target scatterers beyond of far side of the wall is beyond the scope of this article.

C. Discussion

The performance of the method depends on the signal-to-noise ratio of the scattered electric field and the frequency of the source excitation. Some types of walls are poor reflectors at low microwave frequencies resulting in very weak scattered fields. To study this phenomenon, we repeated the exercise on a 0.5-cm-thick plywood wall, as shown in Fig. 10(a). In this case, we are unable to reconstruct the dielectric profile, as shown in Fig. 10(b). This is because the plywood sheet is mostly transparent to the electromagnetic field at 2.4 GHz, resulting in almost negligible scattered returns. A simple method to overcome this limitation is to increase the frequency of the source excitation. Some types of walls are poor reflectors at low microwave frequencies resulting in very weak scattered returns. A simple method to overcome this limitation is to increase the frequency of the source excitation. Unfortunately, such walls do not cause significant distortions to through-wall radar signatures, and hence, it is not imperative to remove the wall effects.

In all of our studies, the walls have been assumed to be uniform along with the height. Hence, the scattered electric field has been gathered across a linear array to capture the diversity in the wall characteristics across the 2-D Cartesian space. In scenarios where it is anticipated to have nonuniform characteristics across the height, the receivers can be placed along different heights to capture the effects of inhomogeneity along with the height. Furthermore, we have assumed that the dielectric constant of the walls is real. When the dielectric constant is complex, the wall properties become dispersive. We believe the complex electrical characteristics can be estimated from scattered fields that arise from wideband source excitation instead of the narrowband source excitation assumed in this article. The study of more complex walls and the corresponding excitation will form the focus of future works. In this article, we have focused on reconstructing the dielectric profiles of the regions beyond the front face of the wall. These regions may comprise multiple layers of inhomogeneous walls including other dielectric bodies (such as indoor furniture), provided that suitable training data are provided to the networks. We have only restricted the scenario to static conditions where there are no temporal variations in the scattered electric field due to dynamic bodies. The estimation of the profiles of dynamic target scatterers beyond of far side of the wall is beyond the scope of this article.

VI. Conclusion

In this article, we proposed GAN-based methods configured with time/frequency-domain input scattered electric field data and ANN or CNN hidden layers to solve the EIS problem to estimate wall characteristics from scattered electric fields. We experimentally validated these methods using both simulations and measurements. The results clearly demonstrated the effectiveness of the proposed methods in reconstructing high dielectric profiles in the scattering region of interest when compared to classical EIS methods. The use of two neural networks in an adversarial manner results in longer training times than other deep-learning-based algorithms with single neural networks. However, they enable accurate and fast reconstruction of dielectric profiles of walls during the test. Furthermore, the use of convolutional filters within the neural networks increases the training time but improves the accuracy during testing. The main advantage offered by the GAN-based algorithms is the limited requirement of a large volume of diverse training data. This means that the algorithm can be tested on real-world walls that are significantly different from those used during training. Our key contribution was to show how neural networks trained with simulated electric field data are useful for estimating the...
dielectric profiles and thickness of actual walls. However, when the walls are thin and made of materials that are transparent to the source excitation frequency, then the scattered fields are weak, and reconstruction is not possible. Fortunately, these types of walls do not significantly distort radar signatures and do not require reconstruction.

APPENDIX A

In this appendix, we discuss the convergence of GAN. Later, we discuss the experiments that were performed to determine the design parameters of the proposed algorithms. We consider two types of parameters: 1) radar parameters that include the number and position of the radar antennas with respect to the walls and 2) GAN network hyperparameters, such as the number of layers, the learning rate, and the dropout.

A. Convergence of GAN

The standard GAN is well known for its problem of modal collapse or instability where the generator synthesizes a single (or few) output images no matter the diversity in its input data. The conditional GAN that we have adopted in this article overcomes this instability problem by using data from a labeled class during training. In our case, this is the scattered electric field \( E_z \) from a known dielectric profile \( \varepsilon_r \) as shown in the objective function in (1). During GAN training, the iterations on the objective function are carried on until the system performance is observed to be effective or when the mean square error (MSE) loss \( ||\varepsilon_r - G_\theta(E_z)||^2_2 \) converges to a low value. For visualization purposes, we show the reconstructed dielectric profiles of some samples across multiple epochs in Fig. 11. The result shows that by the thousandth epoch, the results are very similar to the actual profiles resulting in low MSE.

We have also included the loss graphs of the generator and discriminator for GAN-ANNf, GAN-ANNt, GAN-CNNf, and GAN-CNNt, respectively, in Fig. 12. The figure demonstrates that both the networks converge for both time- and frequency-domain input when they are configured with either the ANN or the CNN. The top row in the figure represents the discriminator’s real and fake losses, while the bottom row represents the training loss of the generator for 1000 epochs. For all the figures, the generator loss is very high (outside the graph) in the first epoch and then rapidly falls and then ultimately settles to a value around 5 for the ANN-based GAN and around 1 for the CNN-based GAN. The discriminator losses for both real and fake data converge around 0.5, indicating that training convergence has been achieved [41].

Note that even further improvements in the GAN output may be realized by incorporating penalty functions directly within the objective function in (1) by

\[
\min_{G_\theta} \max_{D_\phi} V(G_\theta, D_\phi) = \min_{G_\theta} \max_{D_\phi} \log(D_\phi(\varepsilon_r)) + \log(1 - D_\phi(G_\theta(E_z))) + \beta ||\varepsilon_r - G_\theta(E_z)||^2_2. \tag{3}
\]

Our preliminary results with this framework show us that through the appropriate selection of the hyperparameter \( \beta \), we are able to realize an average NMSE as low as 0.002. This suggests that the study of the impact of such penalty functions within the GAN framework may be a future research direction for inverse scattering problems.

B. Radar Parameters

1) Number of Receivers: First, we consider the effect of the number and position of the receivers on the performance. We consider the simulation setup shown in Fig. 3, where the scattered electric field is gathered at ten receiver positions that are spaced half-wavelength apart. In our experiment, we consider five scenarios wherein the data from a subset of the ten receivers are considered in increments of two, as shown in Fig. 13. In other words, in the first scenario, data from receivers 1 and 10 are considered. Then, in scenario 2, data from receivers 1, 3, 8, and 10 are considered, and so on. In each case, we ensure that the receivers span the entire aperture space. Note that the number of receivers is increased across the five scenarios systematically to include the receivers selected for the previous case. The experimental results for the NMSE for each case are presented in Table VI for GAN-ANNf and GAN-ANNt. Similar trends are observed for GAN-CNNf and GAN-CNNt and, hence, are not reported here. We observe an improvement in the NMSE with the increase in receivers. This may be attributed to increasing information regarding the scattering features within the wall for both GAN frameworks. Further increase in the number of receivers is challenging from a practical deployment standpoint due to requirements of very low interelement spacing.

![Fig. 11. Dielectric profile generated using the generator. The profiles in the rows regeneration ability of the GAN.](image)

| Number of receivers | GAN-ANNf | GAN-ANNt |
|---------------------|----------|----------|
| 2                   | 0.56     | 0.50     |
| 4                   | 0.54     | 0.51     |
| 6                   | 0.51     | 0.55     |
| 8                   | 0.47     | 0.39     |
| 10                  | 0.23     | 0.25     |

Fig. 11. Dielectric profile generated using the generator. The profiles in the rows regeneration ability of the GAN.
that the NMSE changes very slightly across the three cases, and hence, the performance is not very sensitive to the standoff of the receivers.

C. Network Architecture

We experiment with different numbers of layers and dropout rates in the generator and discriminator neural networks. There are some thumb rules for deciding the network configurations [64], [65]. The total number of hidden nodes is recommended to lie between the size of the input and output layers (the number of hidden nodes should be two-thirds the size of the input layer, plus the size of the output layer); the number of hidden nodes should be less than twice the size of the input layer. Following these rules, we experimented with several different configurations for GAN-ANNf, as reported in Table VIII. The NMSE is studied for the different number of layers, hidden nodes per layer, and for two different dropout rates—0.1 and 0.2. The exercise is similarly repeated for time-domain GAN versions, and the results are reported in Table IX. We also tuned two hyperparameters—the learning rate and the batch size—and report the results in Table X. Similarly, the choices for CNN-based GAN architectures are reported in Tables XI and XII for time- and frequency-domain data, respectively. In all of the above cases, the parameters were heuristically selected, and the search for the parameters was stopped when we obtained an average NMSE below 0.25.
TABLE X
HYPERPARAMETER TUNING FOR BOTH THE ARCHITECTURES FOR ANN ARCHITECTURE

| Hyper parameter | Value | NMSSE |
|-----------------|-------|-------|
| Learning rate   | 0.001 | 0.70  |
|                 | 0.0002| 0.23  |
|                 | 0.0005| 0.27  |
| Batch size      | 16    | 0.23  |
|                 | 32    | 0.24  |

TABLE XI
ARCHITECTURE CHOICES FOR GENERATOR AND DISCRIMINATOR FOR GAN-CNN

| Discriminator | Generator |
|---------------|-----------|
| Filters       | Filters   |
| Kernel        | Kernel    |
| Stride        | Stride    |
| layer1        | layer1    |
| layer2        | layer2    |
| layer3        | layer3    |
| Filters       | 128       |
| Kernel        | 3 x 3     |
| Stride        | 2 x 2     |
| layer1        | 64        |
| layer2        | 32        |
| layer3        | 32        |
| NMSSE         | 0.42      |
| Filters       | 128       |
| Kernel        | 3 x 3     |
| Stride        | 2 x 2     |
| layer1        | 176       |
| layer2        | 64        |
| layer3        | -         |
| NMSSE         | 0.31      |
| Filters       | 128       |
| Kernel        | 3 x 3     |
| Stride        | 2 x 2     |
| layer1        | 5 x 3     |
| layer2        | 3 x 3     |
| layer3        | -         |
| NMSSE         | 0.17      |

D. Effect of Noise Type

In order to examine the effects of the input noise model on the performance of the GAN networks, we have performed experiments with both Gaussian and uniform noise distributions for different variants of GAN for generating dielectric profiles beyond the front face of different walls. In Fig. 14, we present the qualitative comparison of the results for one specific instance of each of the four types of walls considered in our work—the homogeneous wall, the Y-layered wall, the X-layered wall, and the wall with air gaps.

We observe that the generator is able to reconstruct the dielectric profile almost equally well for all the four wall cases, whether the network is trained with uniform noise or with the Gaussian noise. Furthermore, we provide a quantitative comparison for both types of input noise for all the test cases, as summarized in Table XIII. Again, we see that the normalized mean square reconstruction errors are nearly identical for both cases and that the generator is not very sensitive to the type of noise.

Fig. 14. Comparison of noise type for GAN-ANN for (a) homogeneous wall, (b) Y-layered wall, (c) X-layered wall, and (d) wall with air gaps.

TABLE XIII
COMPARISON OF GAN FOR DIFFERENT TYPES OF INPUT NOISE

| Method       | Input type (t/f) | NMSSE | Training Time (min) | Testing Time (s/min) |
|--------------|-----------------|-------|---------------------|----------------------|
| Gaussian noise | f               | 0.23  | 120-150             | 0.015                |
| GAN-ANNt      | t               | 0.25  | 120-150             | 0.015                |
| GAN-CNNf      | f               | 0.20  | 150-180             | 0.015                |
| GAN-CNNt      | t               | 0.17  | 150-180             | 0.015                |
| Uniform noise | f               | 0.25  | 120-150             | 0.015                |
| GAN-ANNt      | t               | 0.24  | 120-150             | 0.015                |
| GAN-CNNf      | f               | 0.21  | 150-180             | 0.015                |
| GAN-CNNt      | t               | 0.18  | 150-180             | 0.015                |

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